# On Learning Parametric Dependencies from Monitoring Data

Johannes Grohmann, Simon Eismann, Samuel Kounev

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05.11.2019

https://se.informatik.uni-wuerzburg.de/

# Software Performance Models



- Performance models are a common approach to predict software performance

**Server system**

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**Server system**

maximize

**Efficiency**

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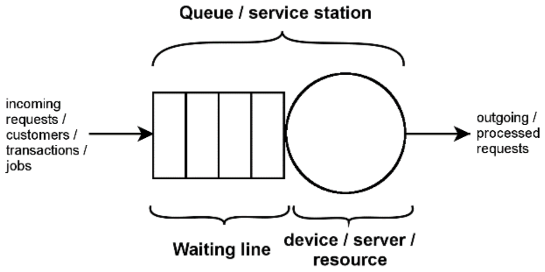
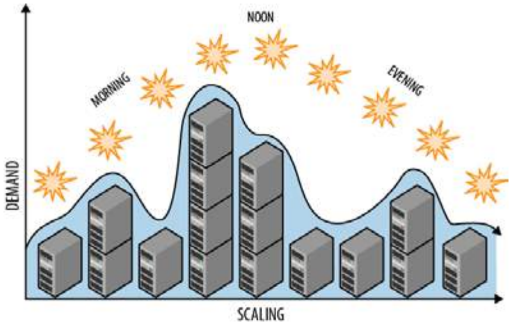



**Performance model**

e.g.




**Auto-scaler**

# Software Performance Models

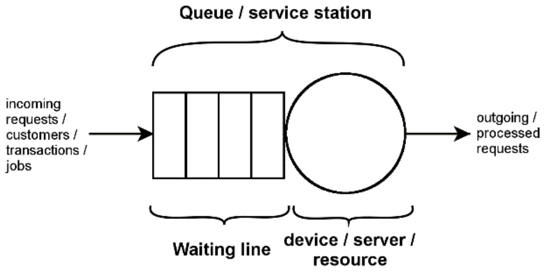


- Performance models are a common approach to predict software performance
- However, correctly modeling a software system is difficult

**Server system**

maximize

**Efficiency**

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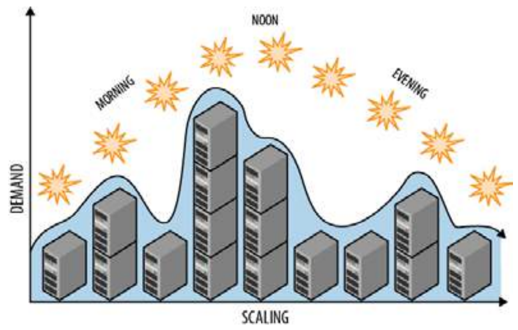


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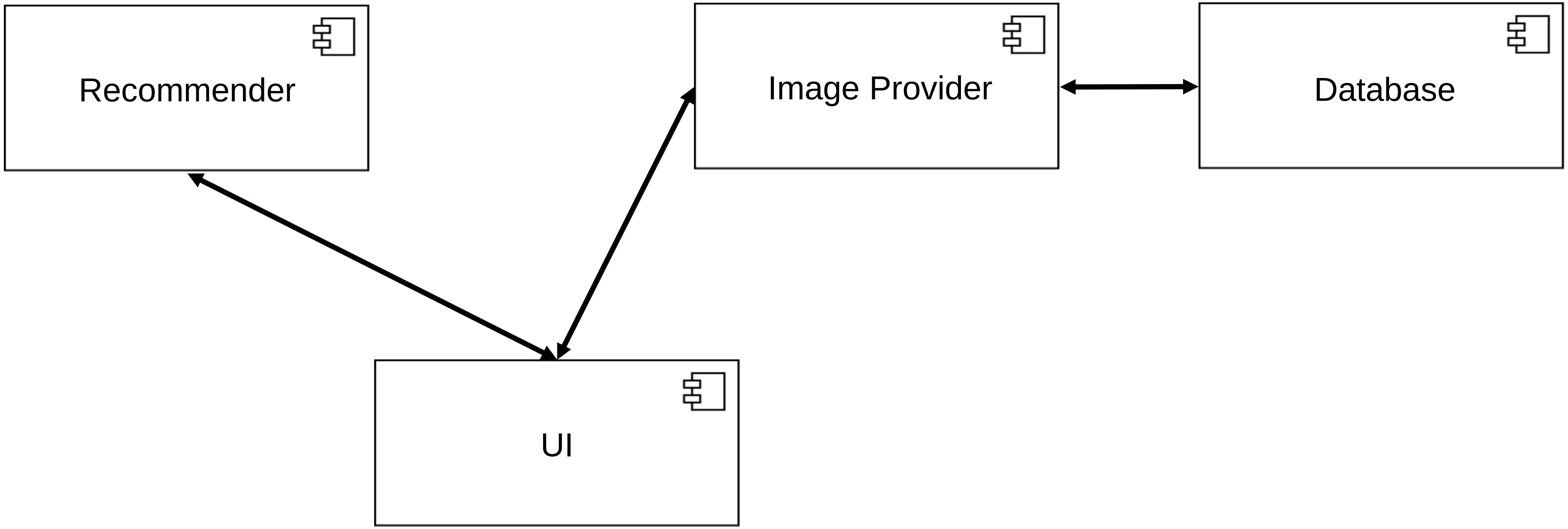
# Parametric Dependencies





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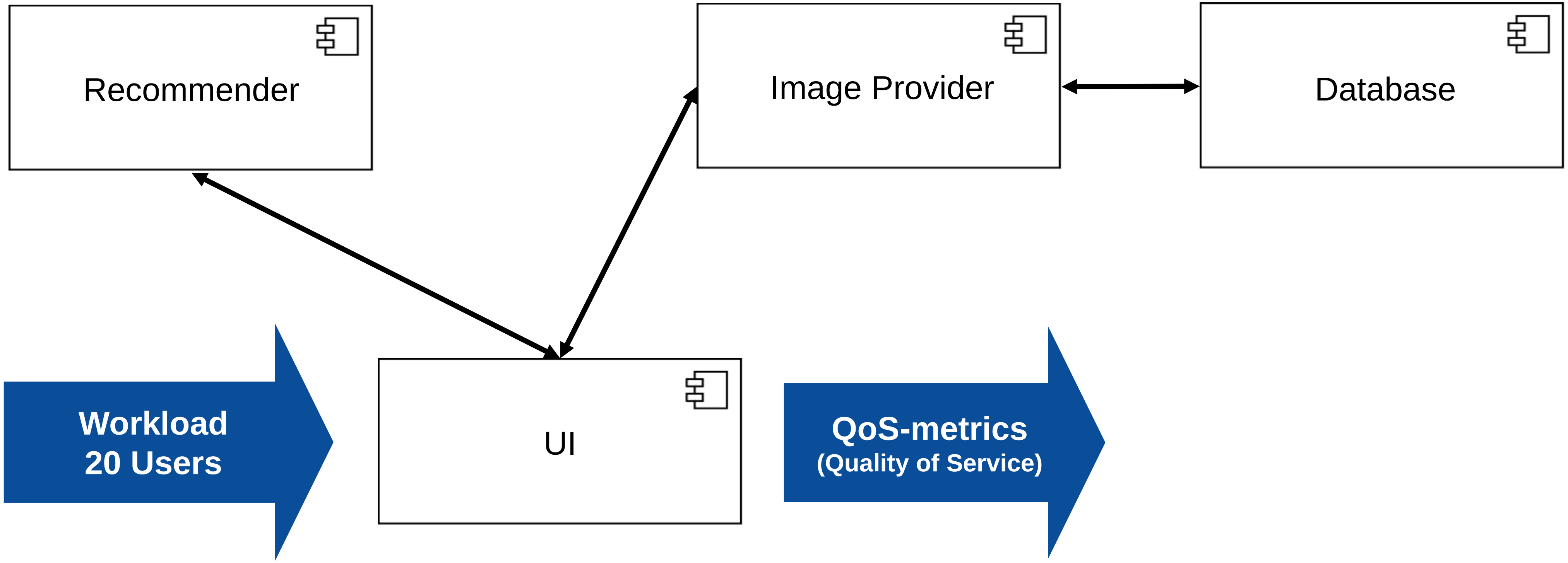

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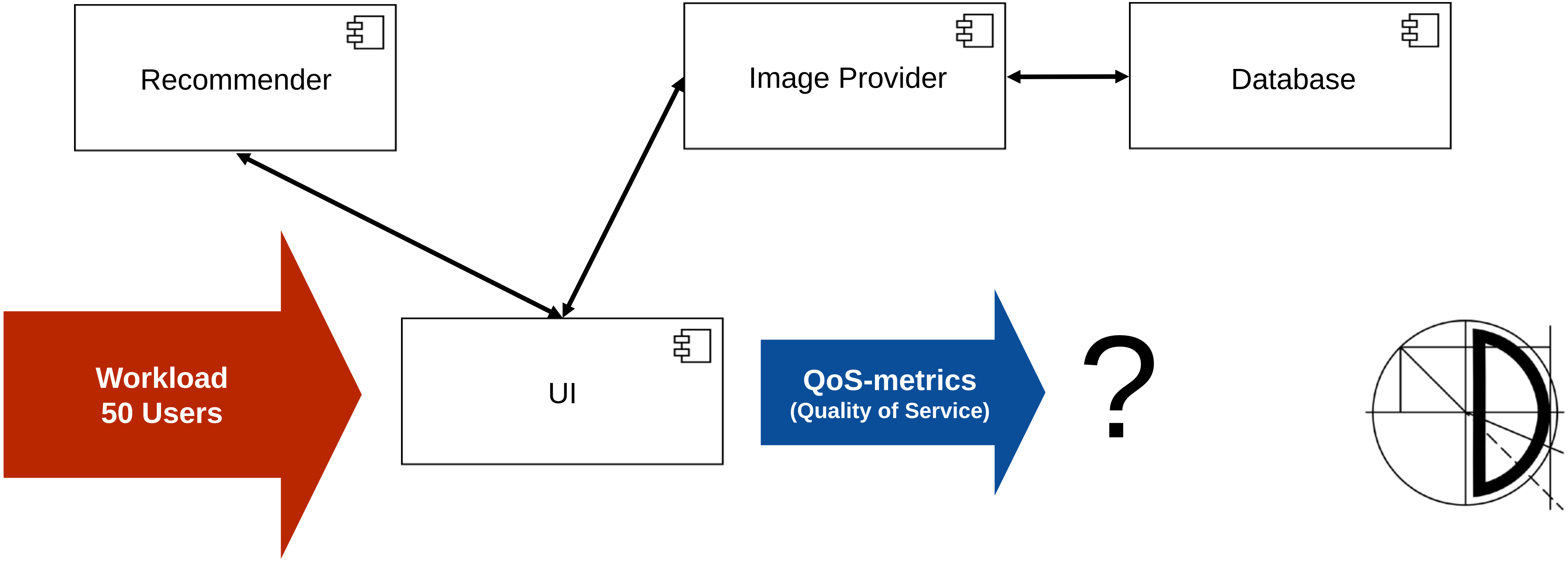
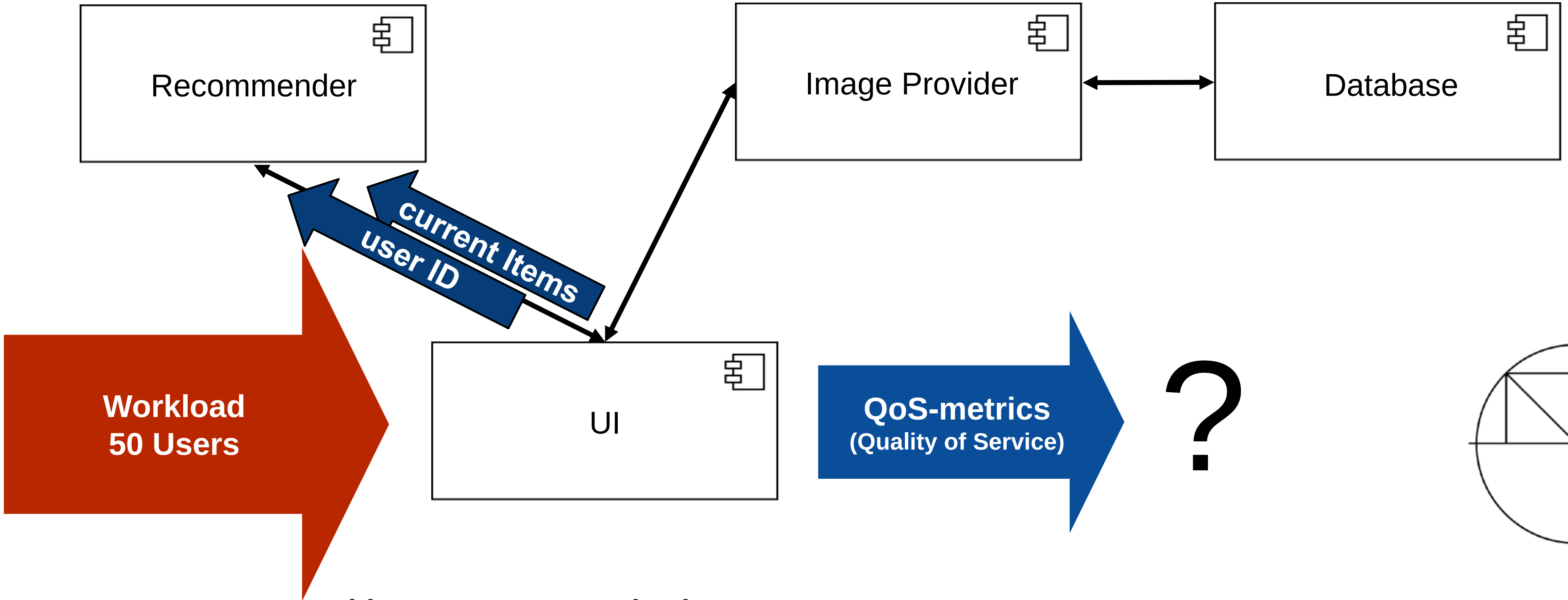


# Parametric Dependencies



- One parameter of performance models are parametric dependencies




ResourceDemand(Recommender)
[milliseconds]

# Parametric Dependencies



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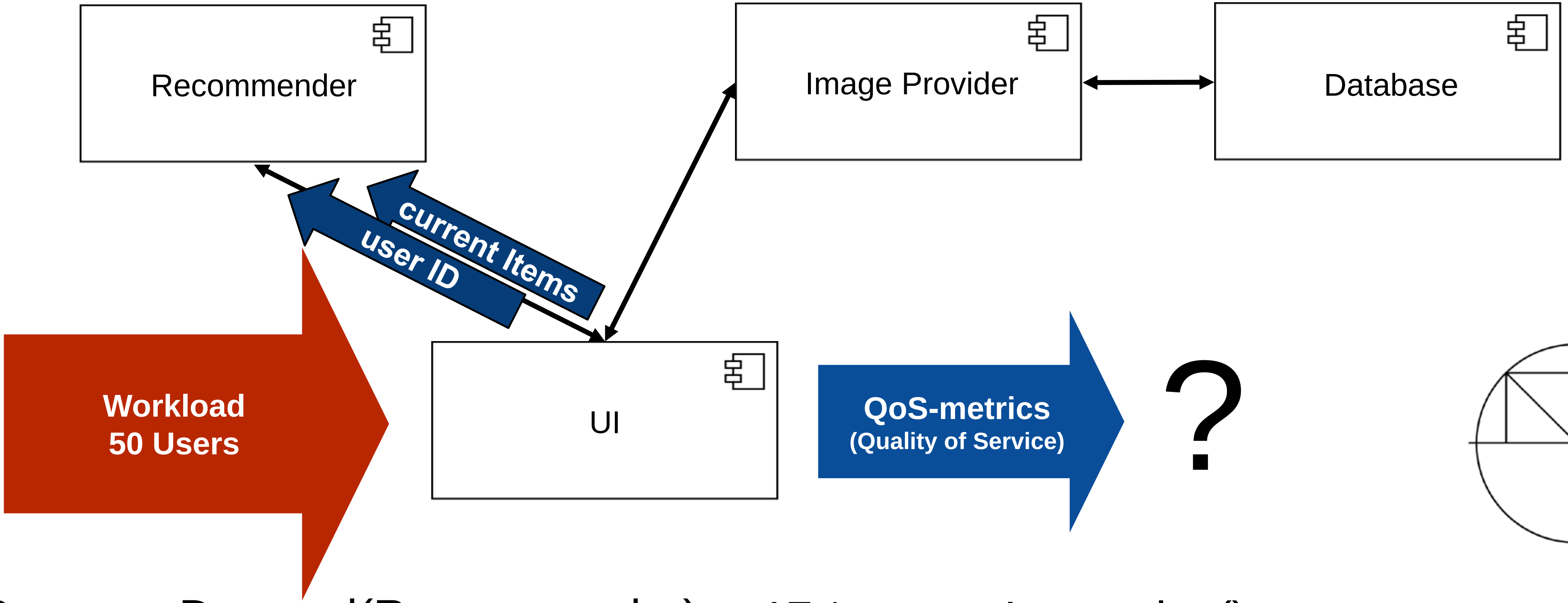


ResourceDemand(Recommender) = 17 * currentItems.size()
[milliseconds]

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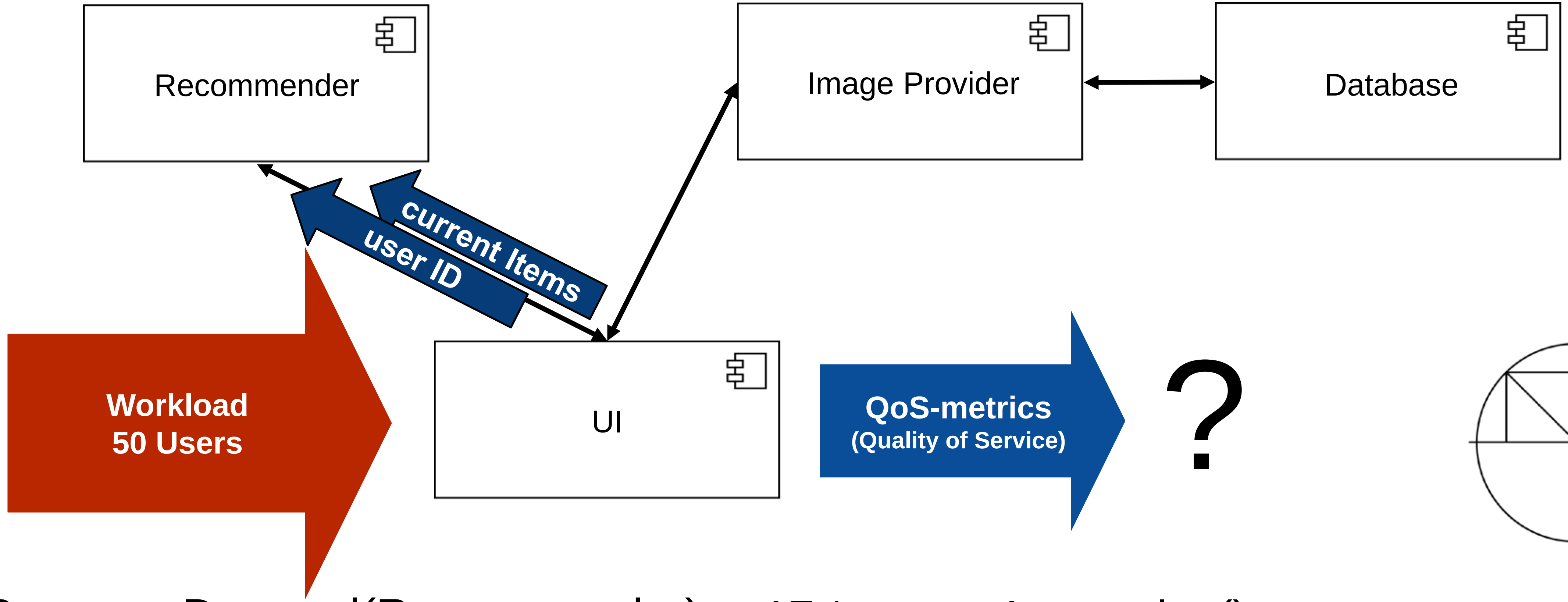


ResourceDemand(Recommender) = 17 * currentItems.size() + 0 * user ID
[milliseconds]

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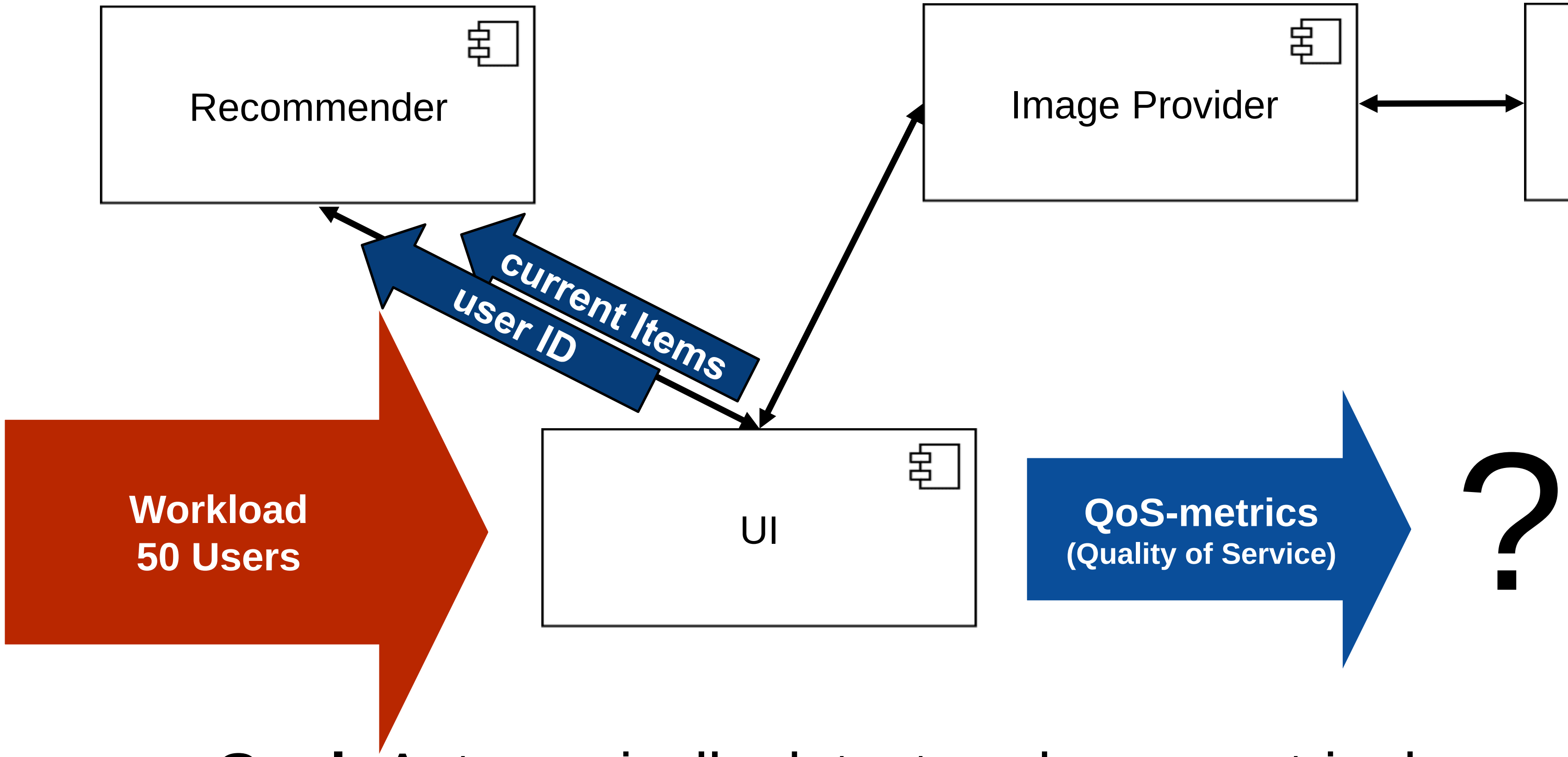
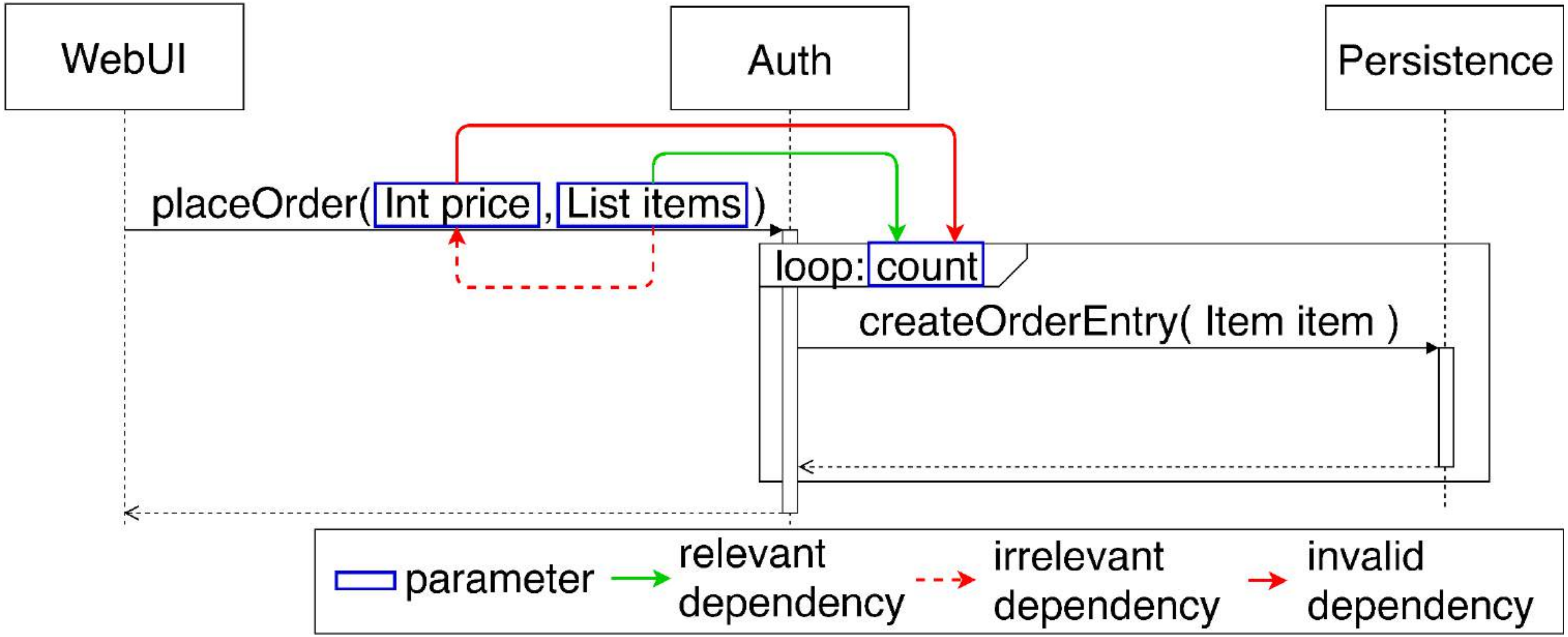



**Goal:** Autonomically detect such parametric dependencies

# Example




WebUI
Auth
Persistence
placeOrder( Int price , List items )
loop: count
createOrderEntry( Item item )
parameter
relevant dependency
irrelevant dependency
invalid dependency

# Related Work



- Krogmann et al. [KKR10] or Mazkatli and Koziolek [MK18] require source code for detection of dependencies. In contrast, our approch is solely based on monitoring data.

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**Monitoring data** → **Model Extraction** [BHK11, WS+17, HW+99, IL+05, MF11] → **Performance Model** → **Parameterization** [SC+15, BHK11, SG+19, RV95, KP+09] → **Parameterized Performance Model**

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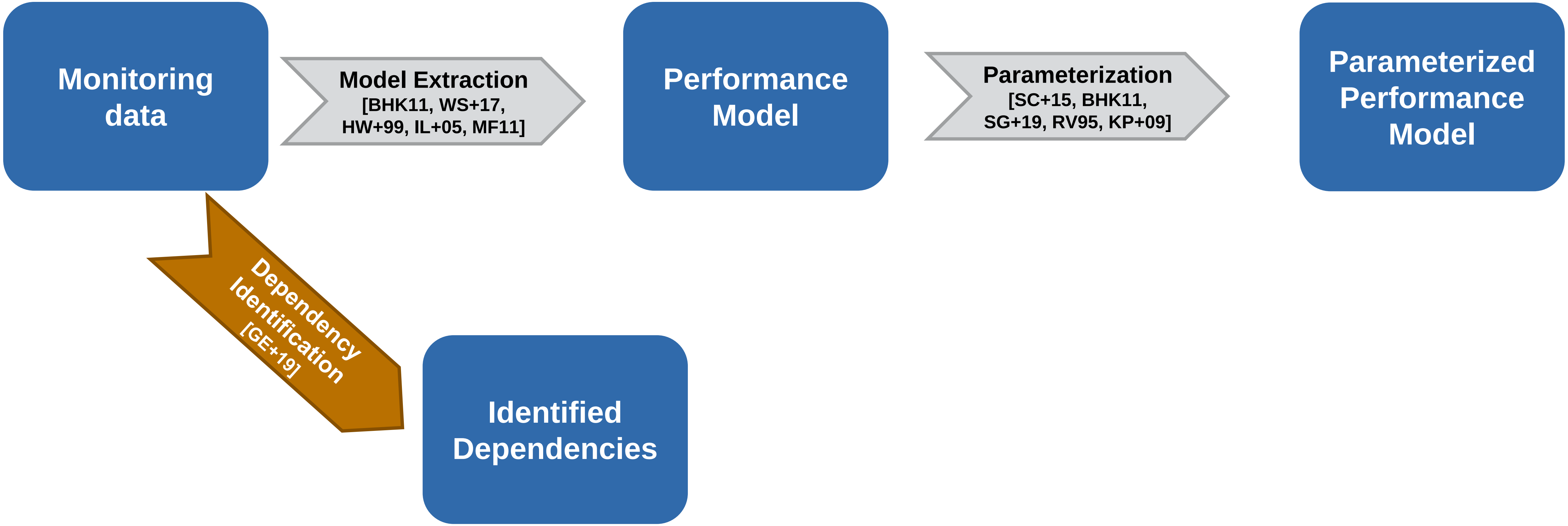

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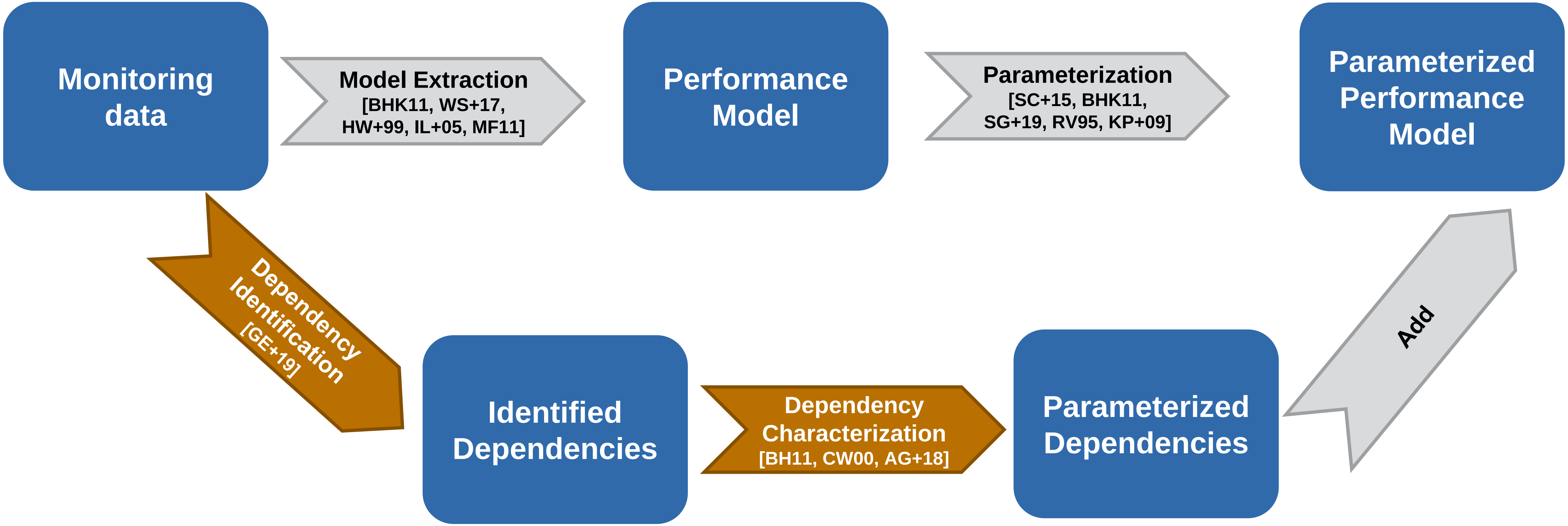

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**Manual identification of parametric dependencies is not always possible, time-intensive and error-prone**

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**Increase model accuracy and expressiveness, additional step towards autonomic model learning**

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| **Problem** | **Manual identification of parametric dependencies is not always possible, time-intensive and error-prone** |
| **Idea** | **Learning of dependencies using standard monitoring data collected during production** |
| **Benefit** | **Increase model accuracy and expressiveness, additional step towards autonomic model learning** |
| **Action** | **Use feature selection techniques for detecting, regression for characterizing the dependencies** |

# APPROACH

# Required monitoring information



- Monitoring data per invocation through Kieker [vHWH12] monitoring
  - Parameter values and types
  - Return value and type
  - Resource demand

Identification parameters

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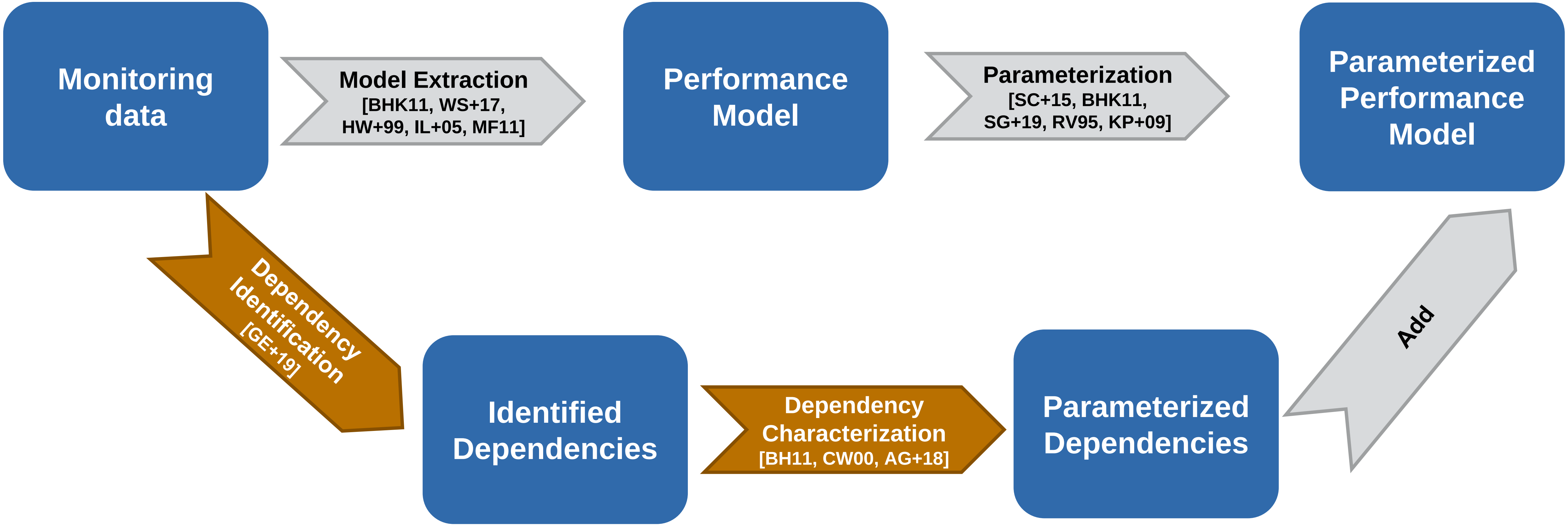
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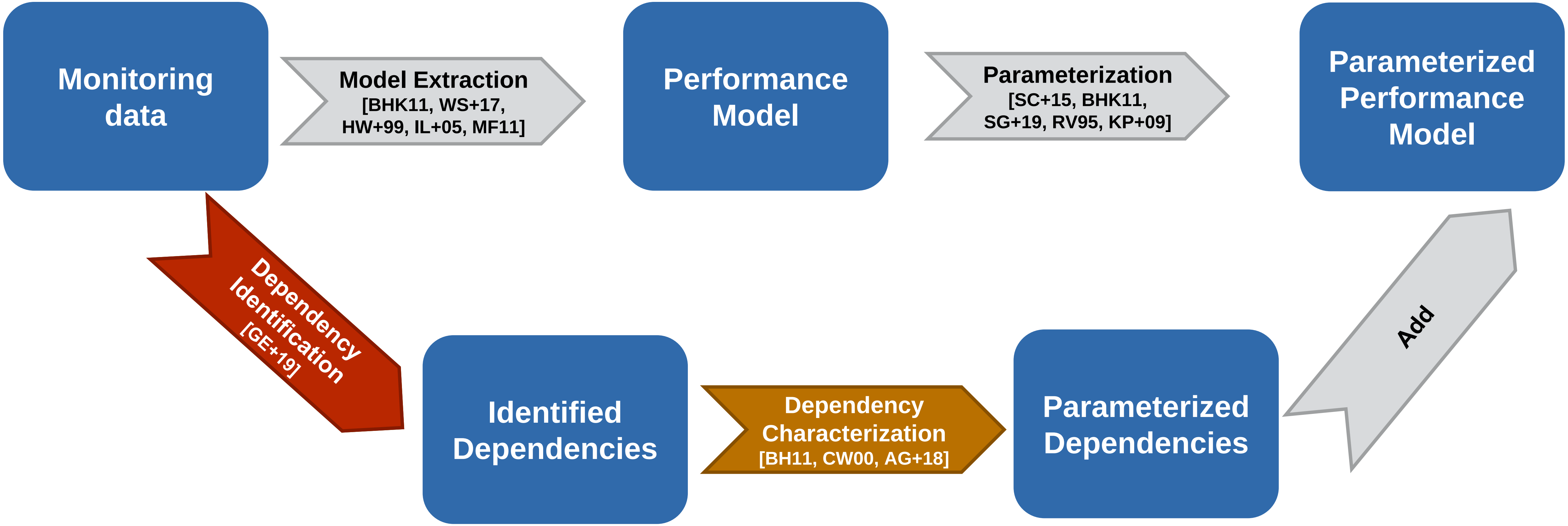
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# Identification approaches



Monitoring Values | Model var.

$$\begin{pmatrix}3\\7\\3\\\dots\end{pmatrix} \quad \dots \quad \begin{pmatrix}8\\23\\95\\\dots\end{pmatrix} \begin{pmatrix}65\\32\\41\\\dots\end{pmatrix} \quad \Rightarrow \quad \begin{pmatrix}65\\32\\41\\\dots\end{pmatrix}$$

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Monitoring Values → Features

Model var. → Target

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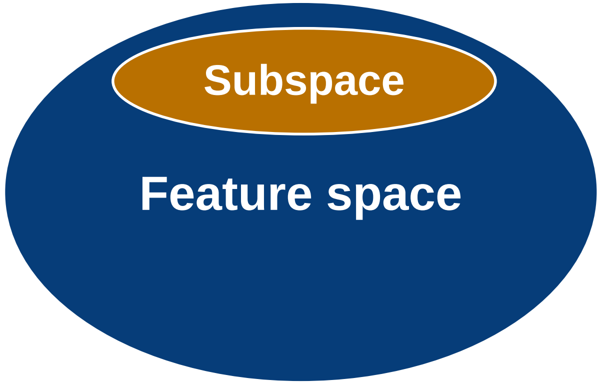

# Identification approaches



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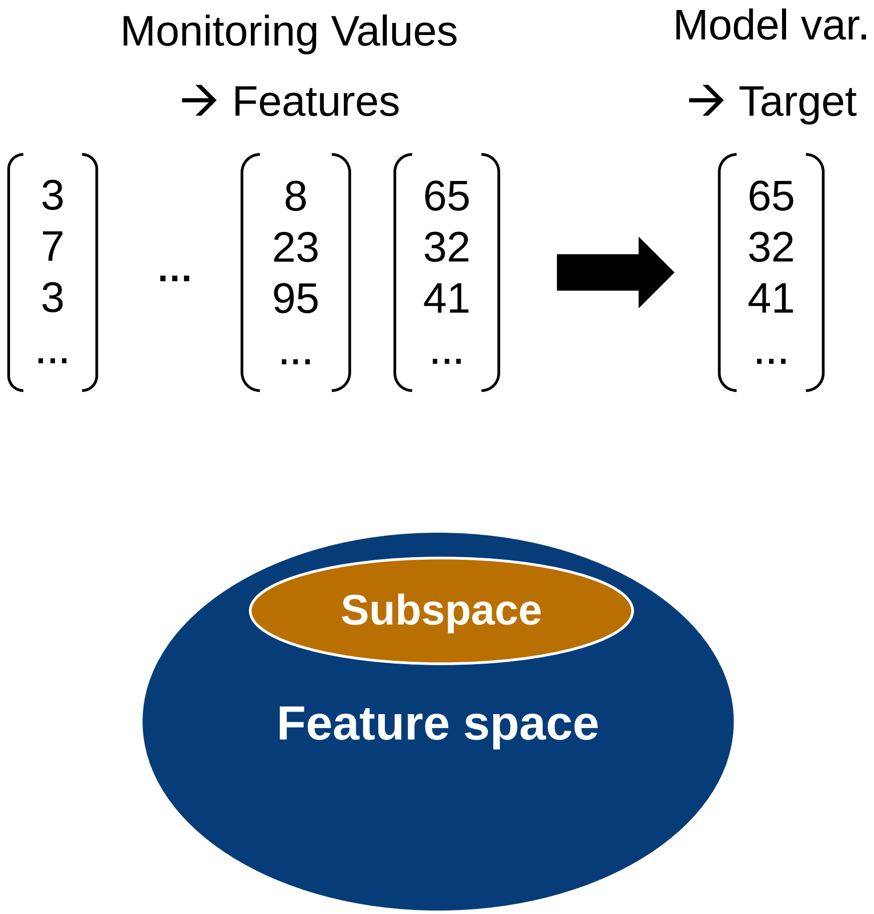
  - Evaluate feature importance during training
  - Selection based on comparison with „noise feature“
  - Algorithm: Random forest [H95]



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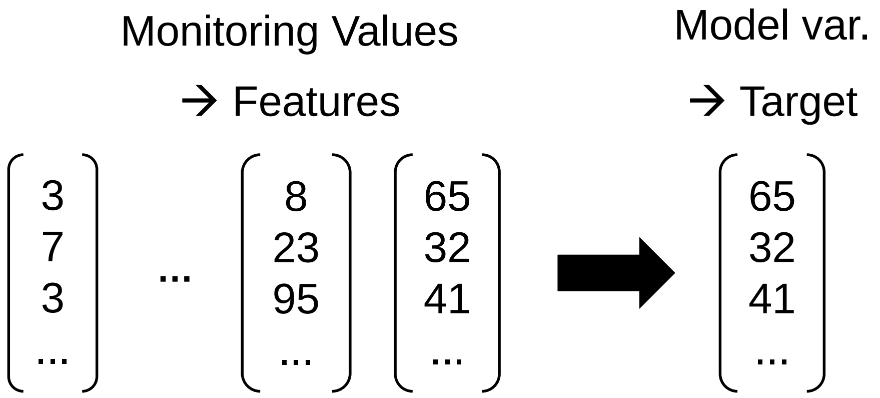
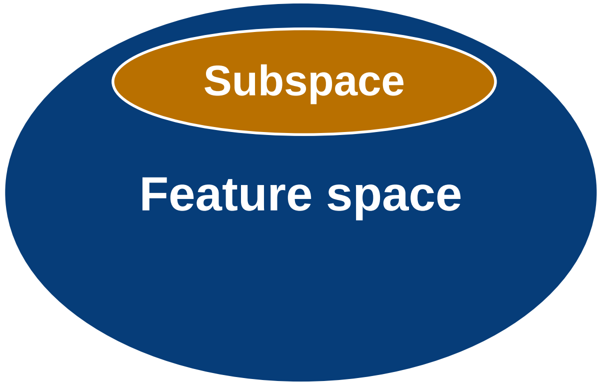



- Wrapper
  - Selection based on accuracy error for a feature subset, compared with a baseline regressor
  - Algorithm: M5 trees [Q+92] and Linear regression



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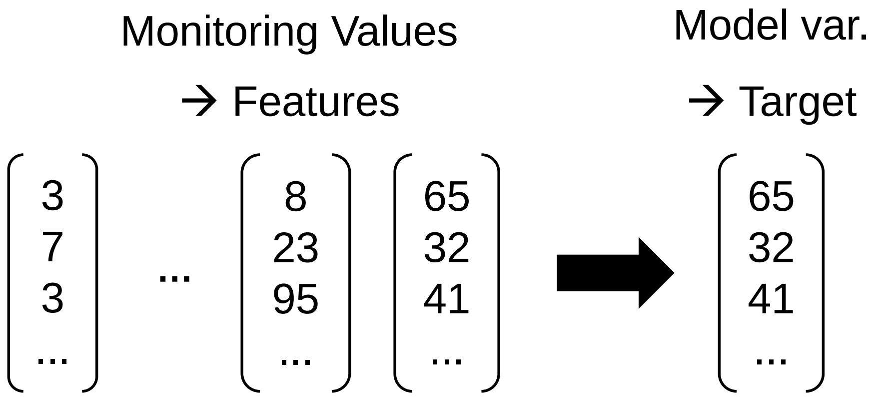


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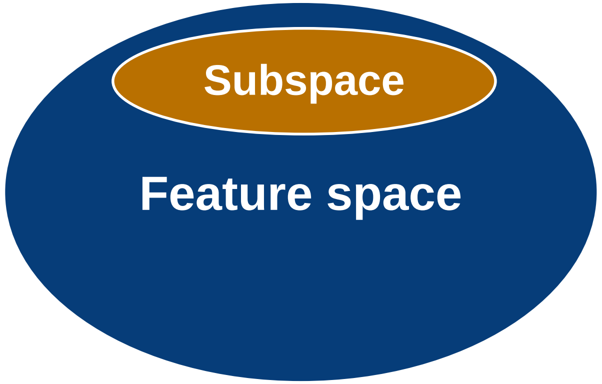
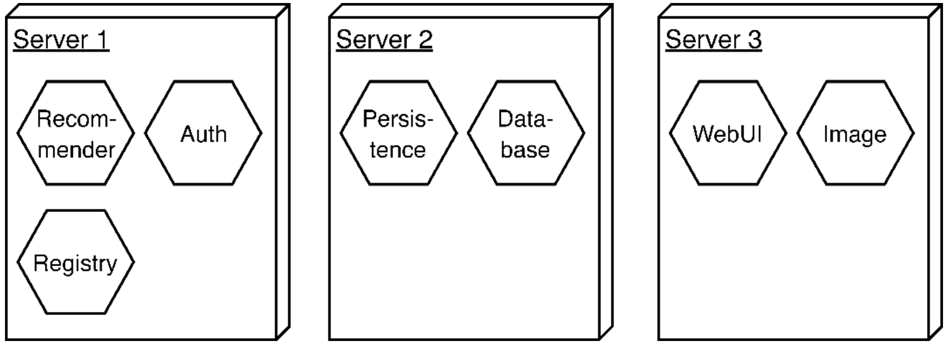
- Filter: Correlation-based
  - Pearson product-moment correlation coefficient (PPMCC)
  - Selection based on threshold for correlation

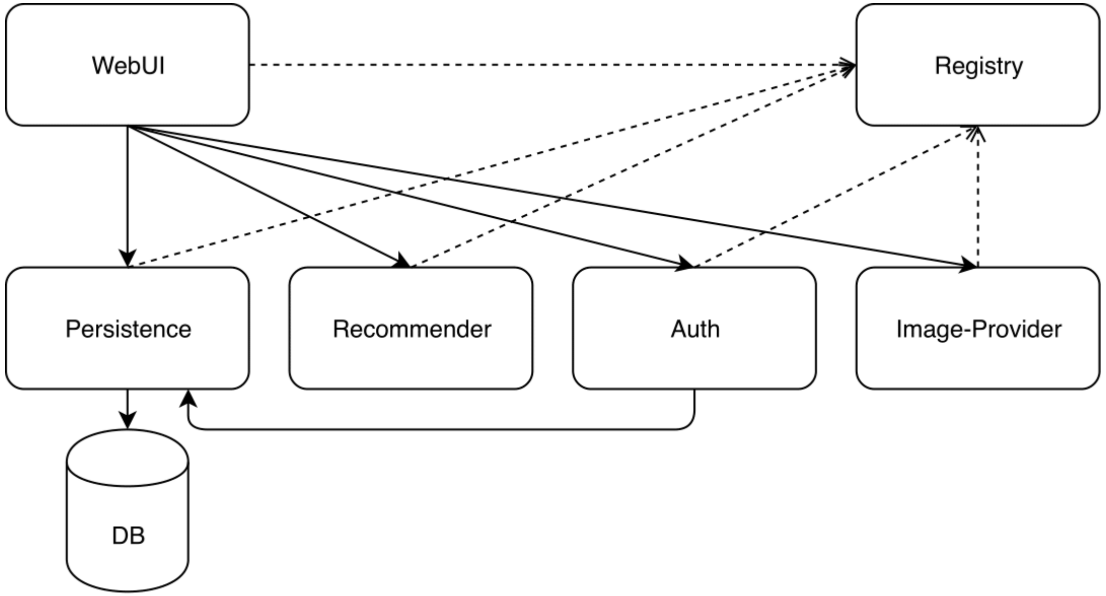


# Evaluation



- Distributed deployment of TeaStore [vKE+18] application



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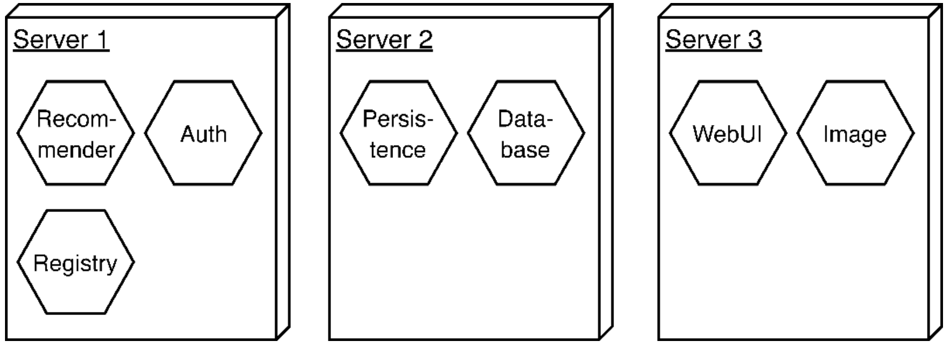
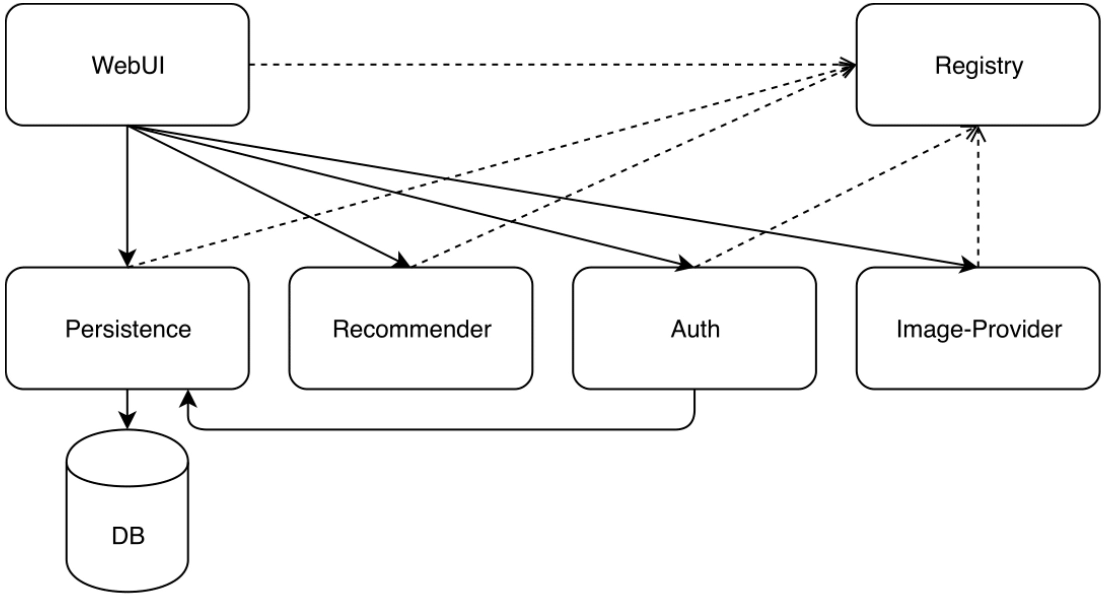
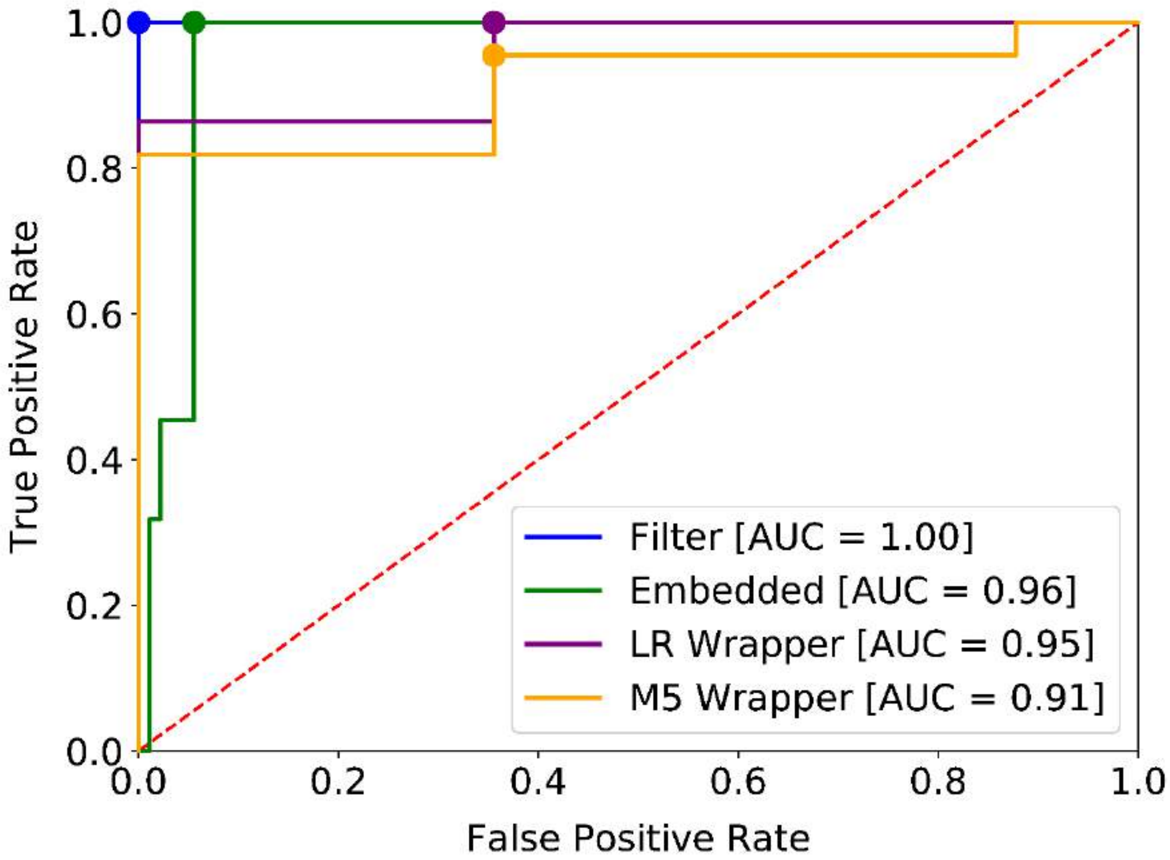



- Locust as load driver with typical behavior of customer
  - Login & logout
  - Browse for products
  - Add products to cart
  - Checkout cart

# Selection Thresholds






- Filter approach outperforms other approaches
- Results are threshold-independent

# Filter Application



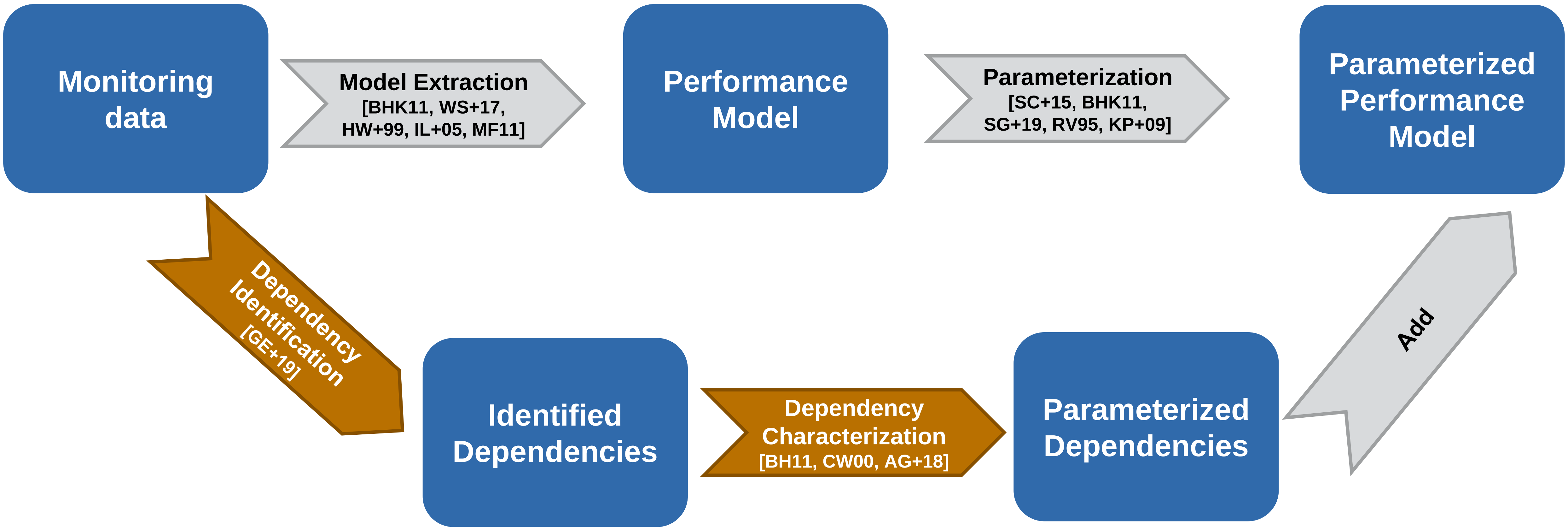
| Filtering Step | Relevant | Irrelevant | Invalid | Total |
|---|---|---|---|---|
| None | 11 | 94 | 5 | 110 |
| Identical (1) | 11 | 45 | 5 | 61 |
| (1) + Correlating (2) | 11 | 35 | 1 | 47 |
| (1) + (2) + Graph-based (3) | 11 | 8 | 1 | 20 |

**In total, 86 irrelvant and and 4 invalid dependencies are deleted.**

**This results in a precision (11 relevant to 1 invalid) of 91.7 %.**

# Overview

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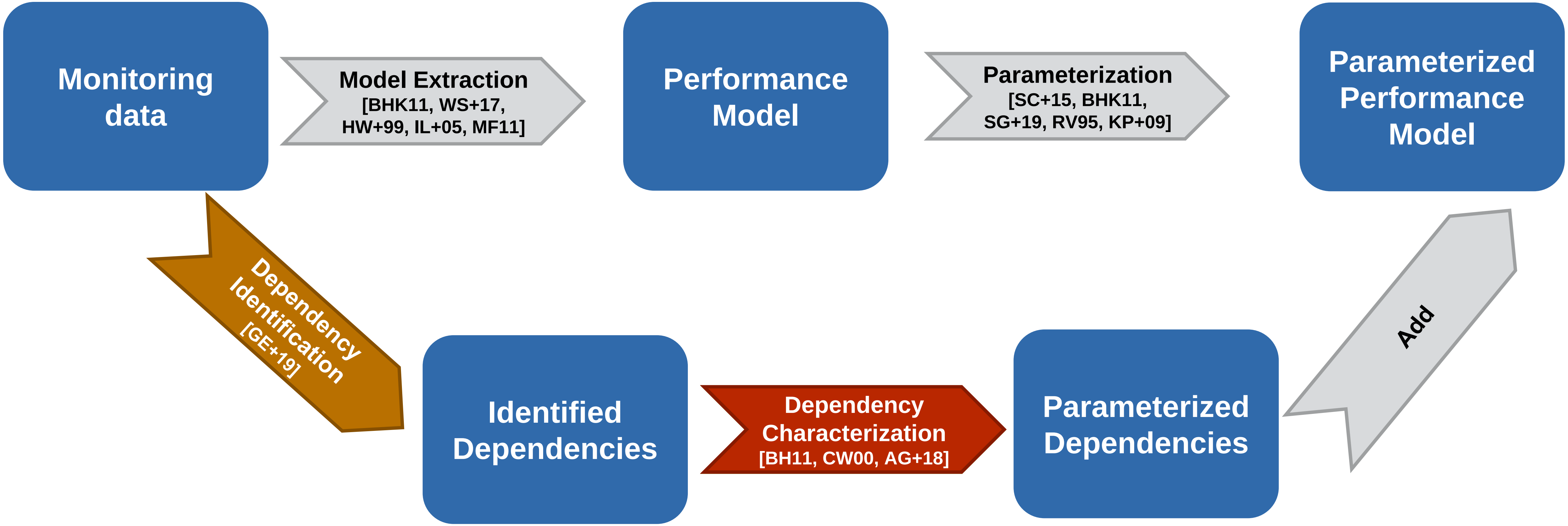
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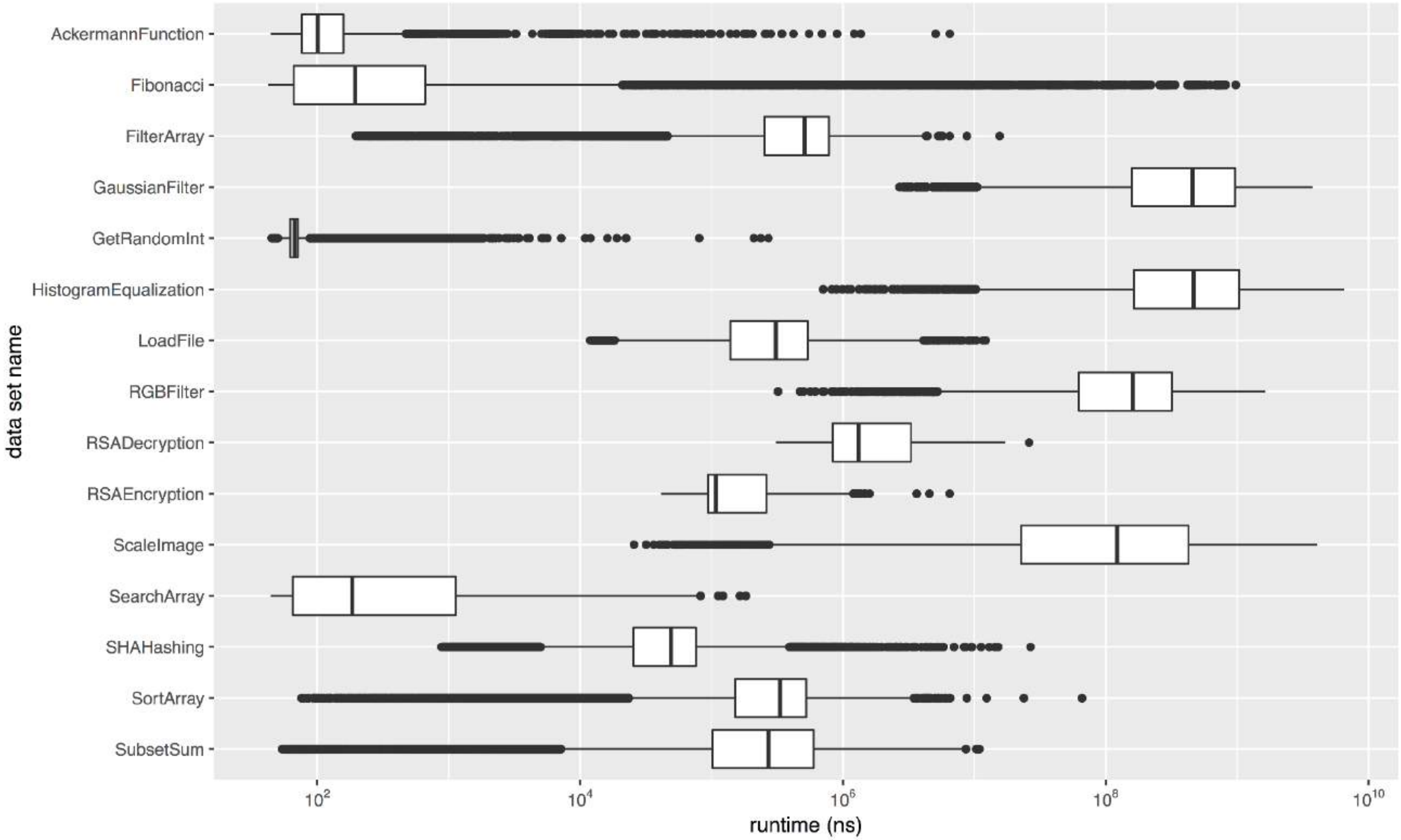
# Dataset Characteristics I





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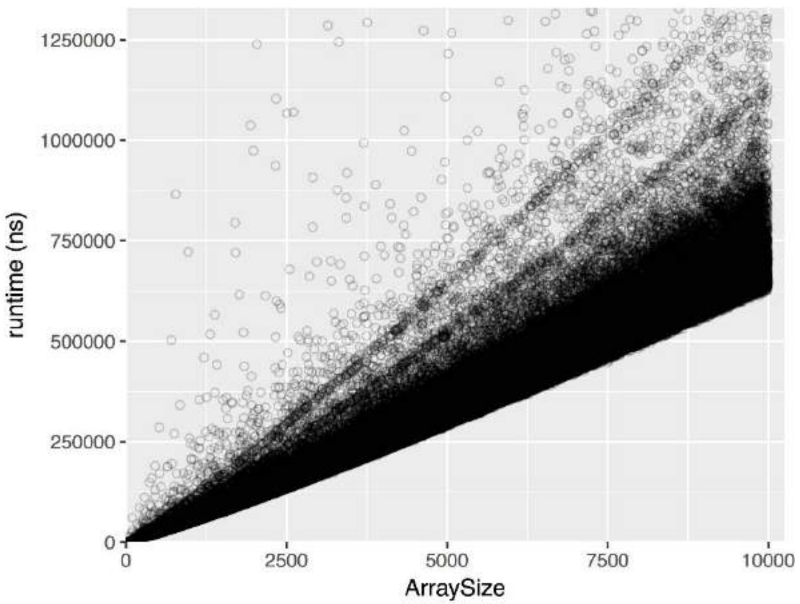
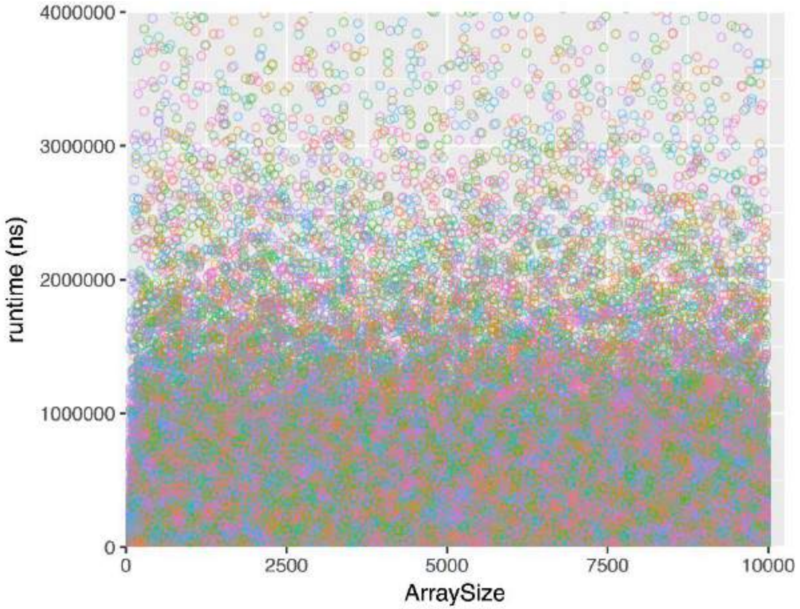
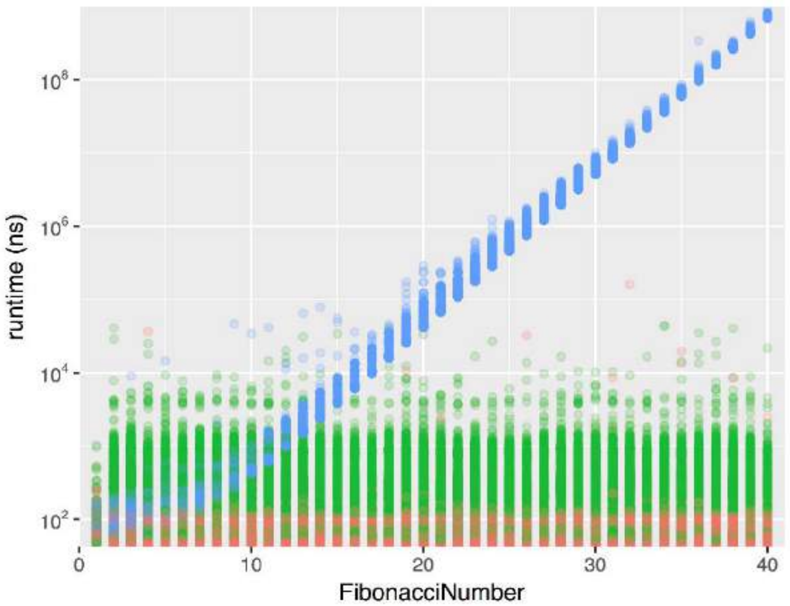



SortArray




SubsetSum

Colors encode defined sum




Fibonacci

Recursive
Optimized recursive
Iterative

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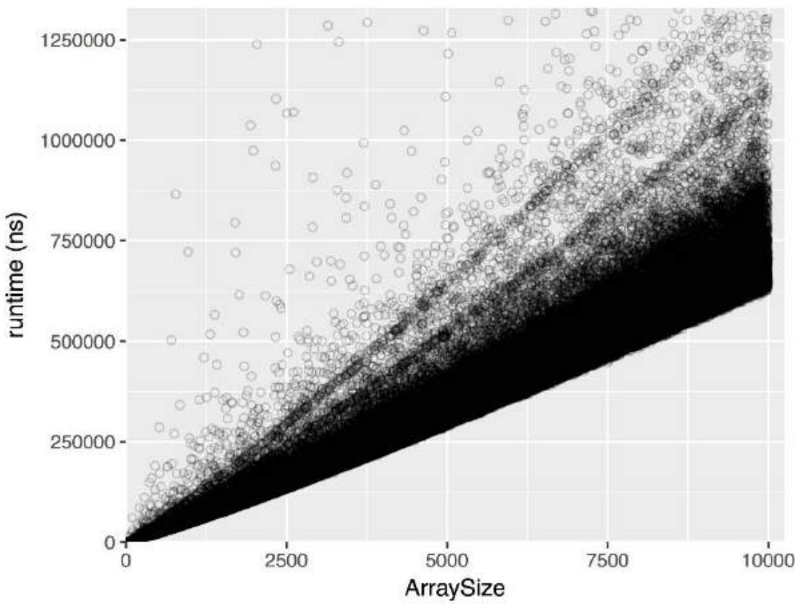


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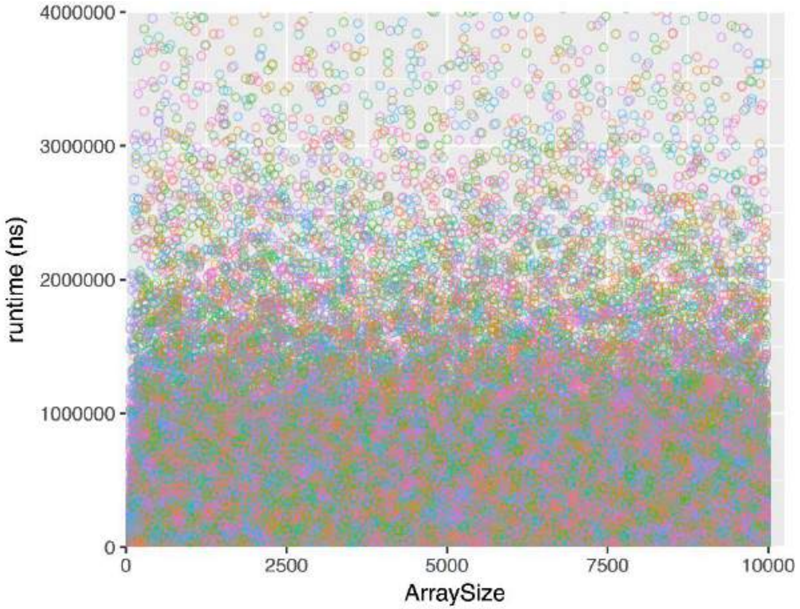


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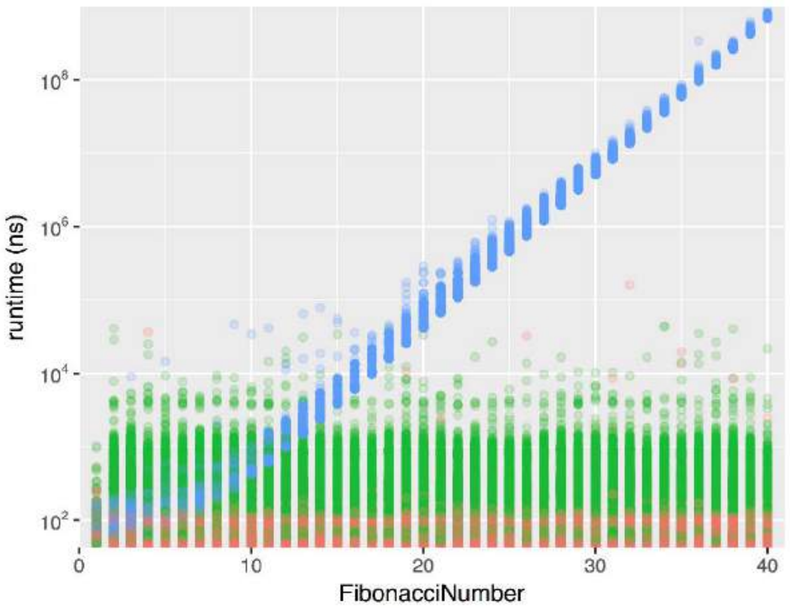


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**The datasets are diverse and varying in terms of number and types of parameters, distribution of runtime (resource demand) and type of dependency.**

# No Free Lunch

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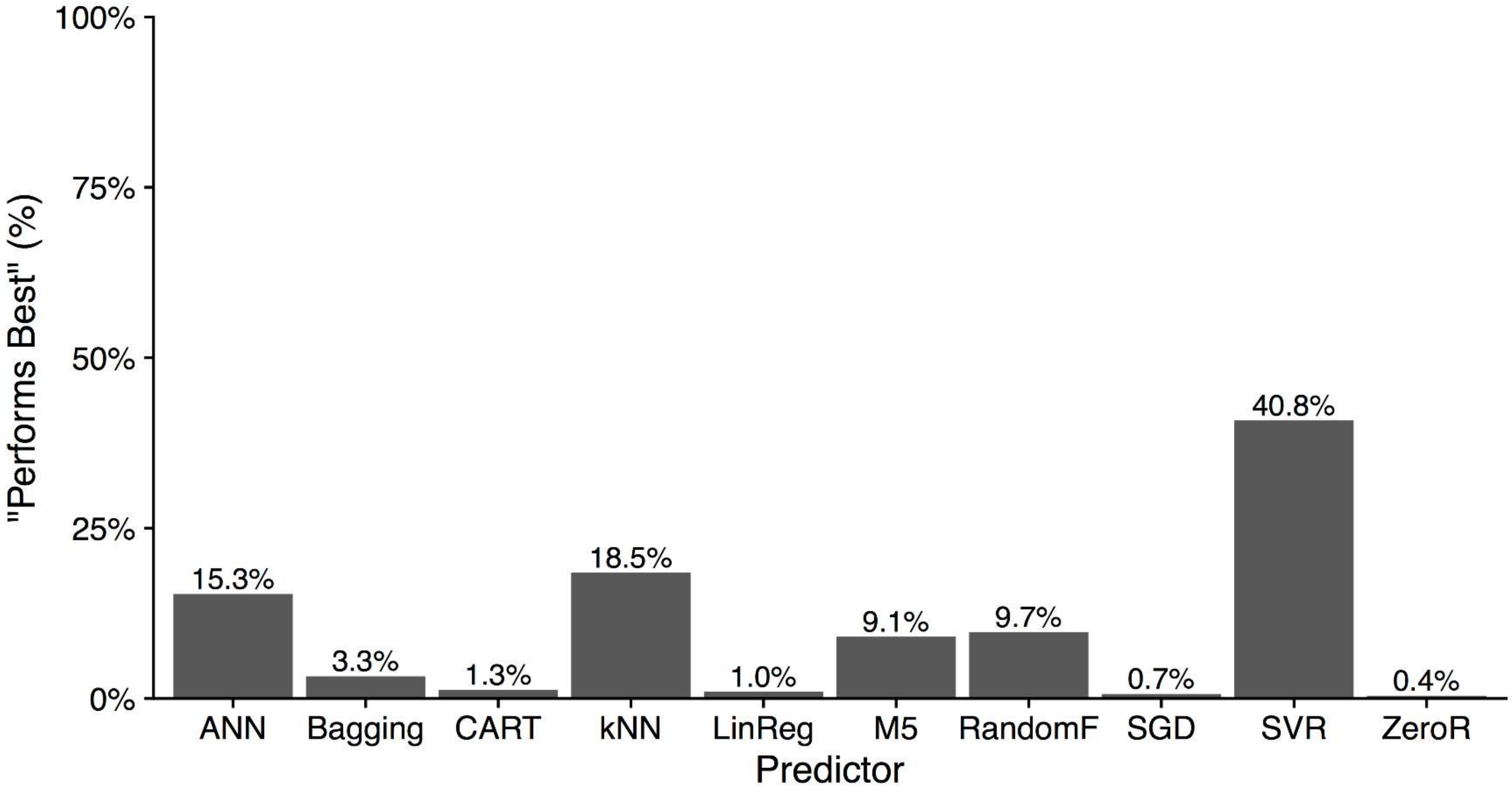

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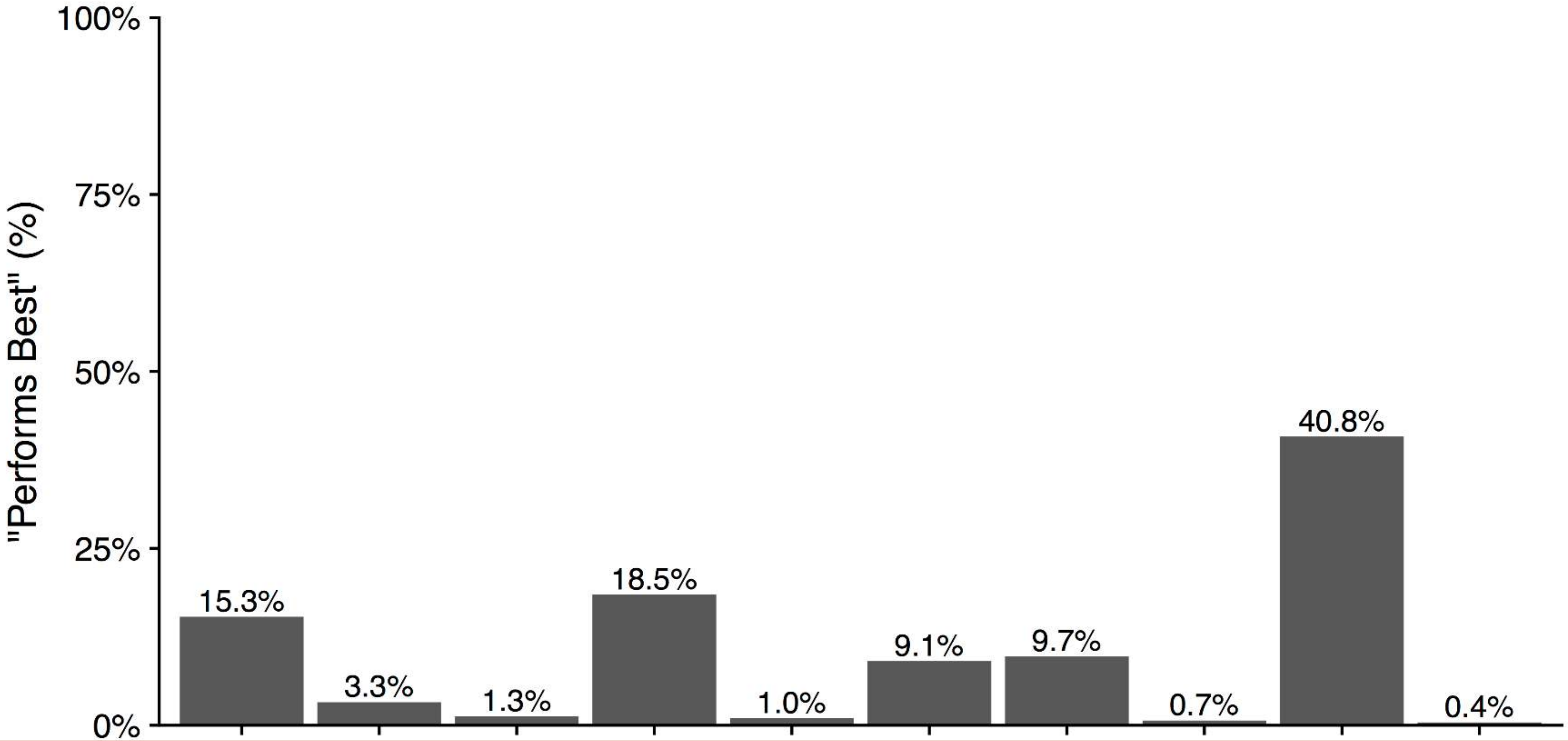
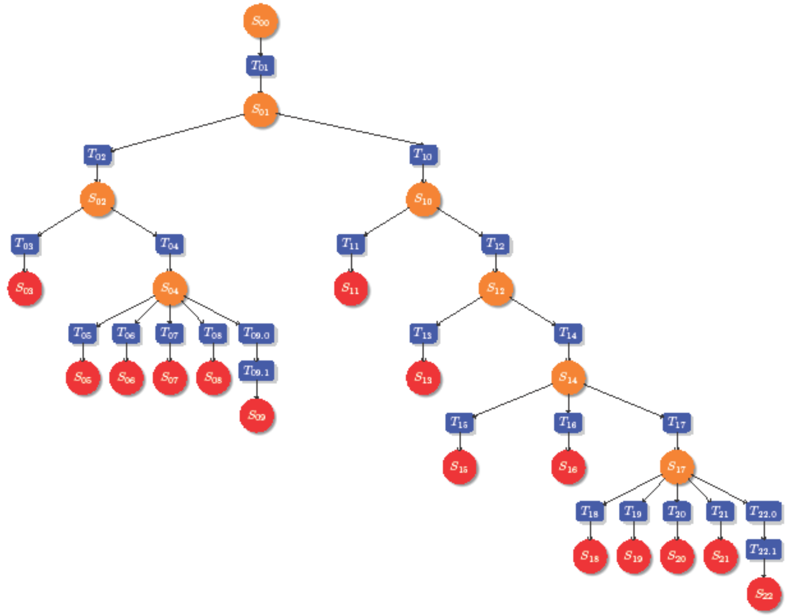



**No Free Lunch for ML approaches! [8]**
**We need a meta-classifier to select the appropriate algorithm.**

# Meta-Classifier



- Using Classification and Regression Trees (CART) to train a Decision Tree on the following features:



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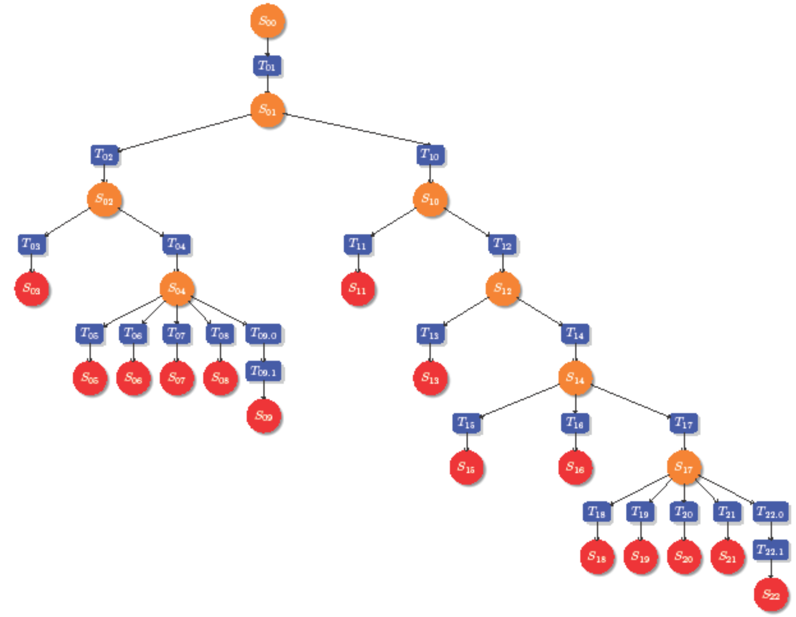
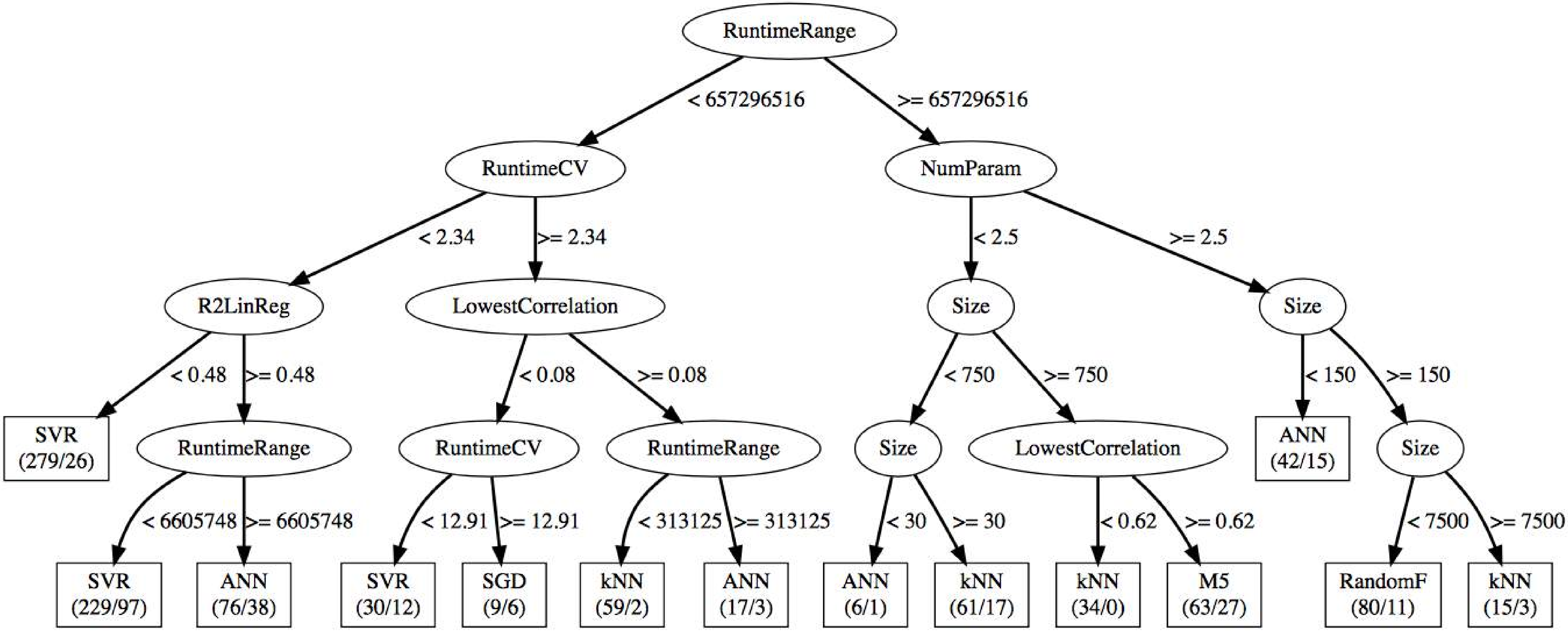


  - Number of training instances (Size)
  - Number of parameters (NumParam)
  - Range of runtime values (RuntimeRange)
  - Coefficient of variance of runtime (RuntimeCV)
  - Highest linear correlation between any input parameter and runtime (HighestCorrelation)
  - Lowest linear correlation between any input parameter and runtime (LowestCorrelation)
  - Coefficient of determination (R2) (R2LinReg)

# Meta-Classifier II





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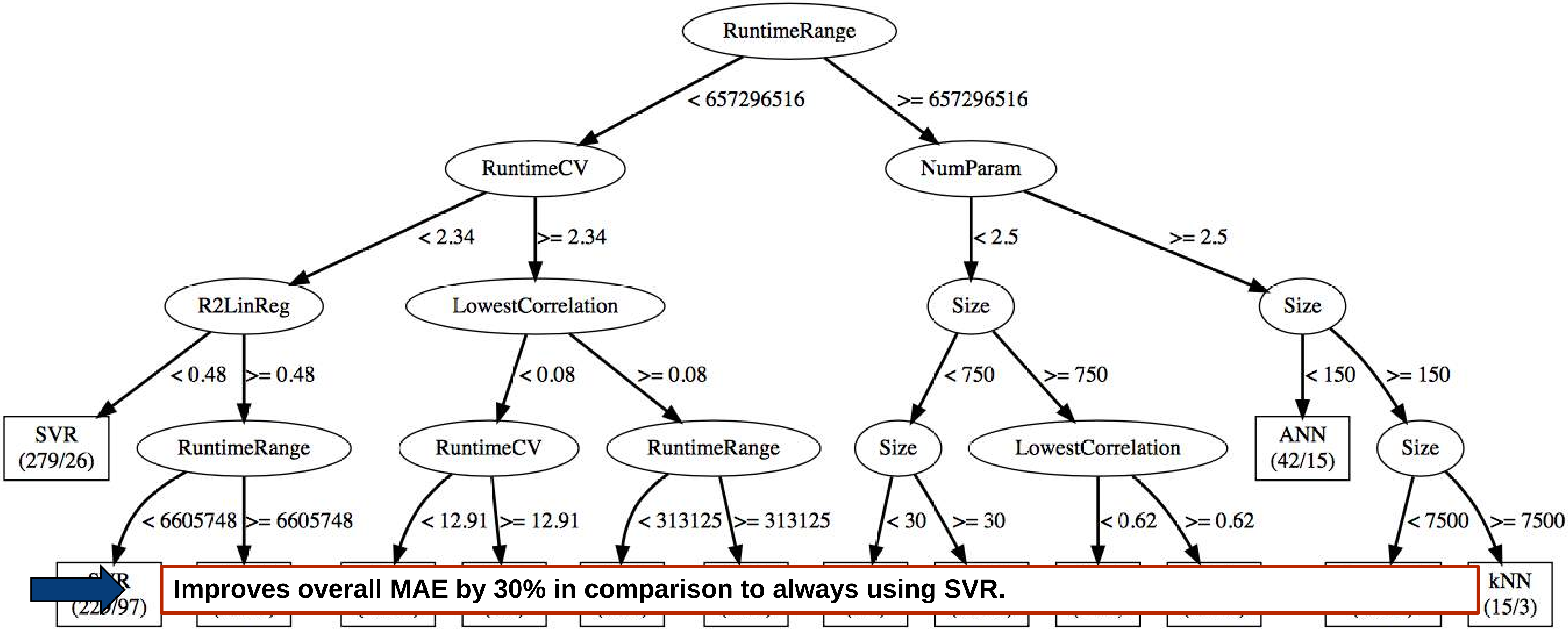


**Improves overall MAE by 30% in comparison to always using SVR.**

# OPEN CHALLENGES

# Monitoring Challenges



- Monitoring data per invocation through Kieker [vHWH12] monitoring
  - Parameter values and types
  - Return value and type
  - Resource demand

  Identification parameters

  - Method signature
  - Entity

  Parameter-related information

  - **Trace id**
  - Execution order index (**EOI**)
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  Trace reconstruction

- Enables reconstruction of call-path trace for resolving aggregations

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**How can the features be extracted?**

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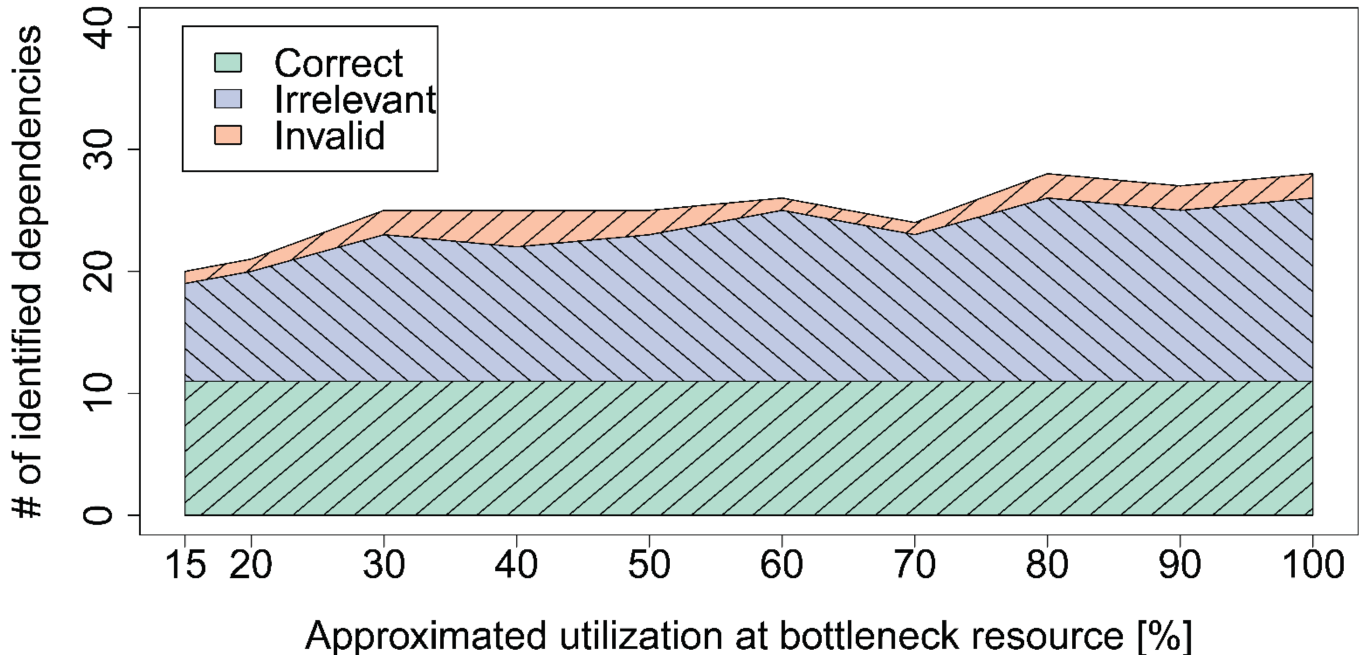
**We can only observe the response time.**

**How can the resource demands be measured?**

- Enables reconstruction of call-path trace for resolving aggregations

# Stability in higher load scenarios





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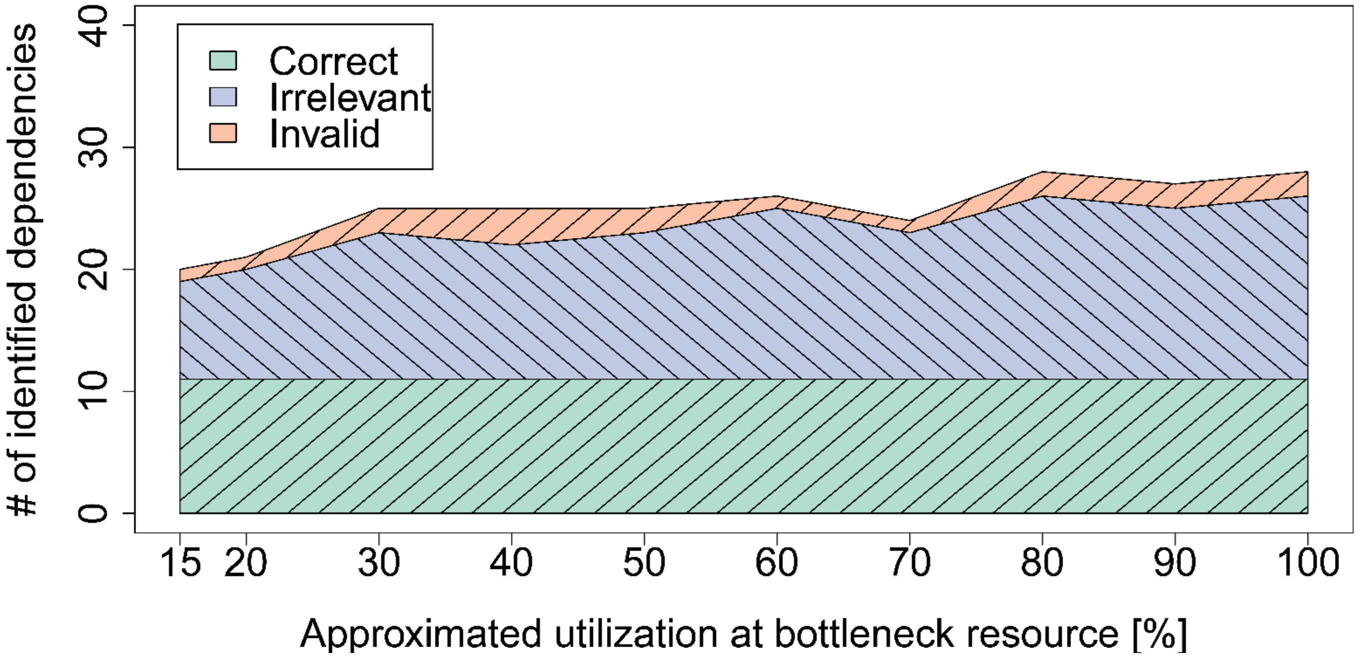
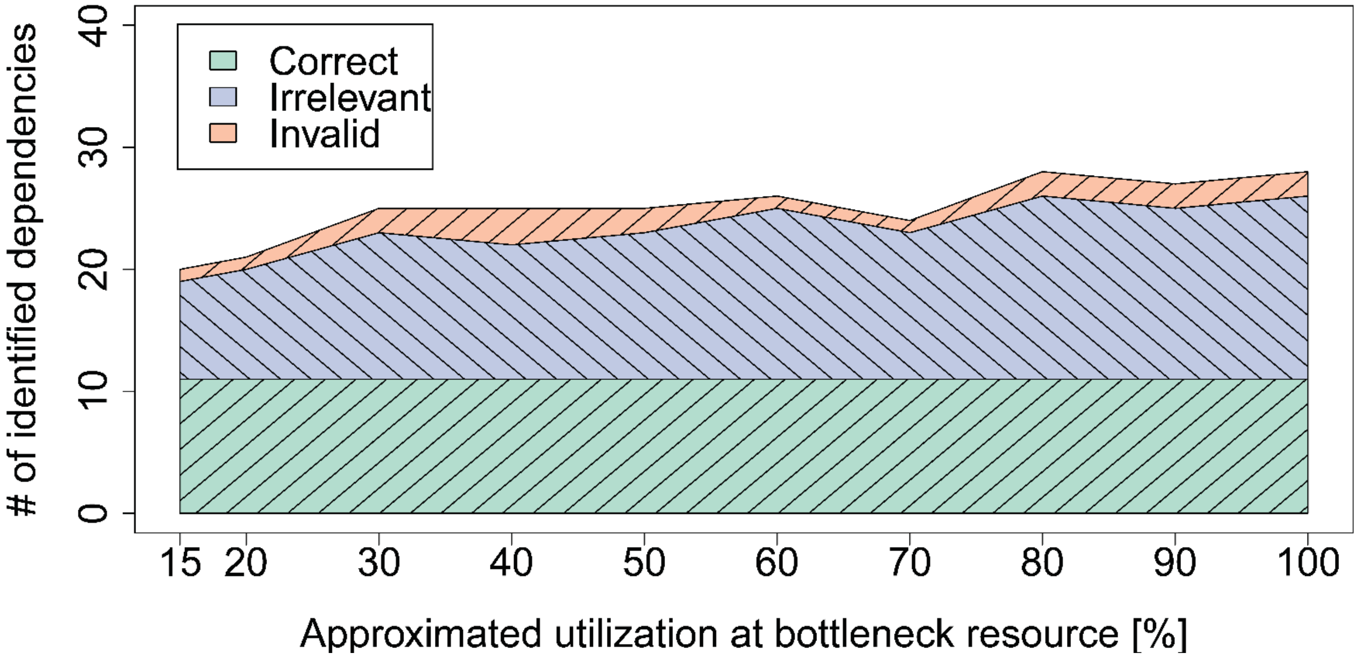



- Higher loads lead to less accuracy; however the effect is light

# Stability in higher load scenarios

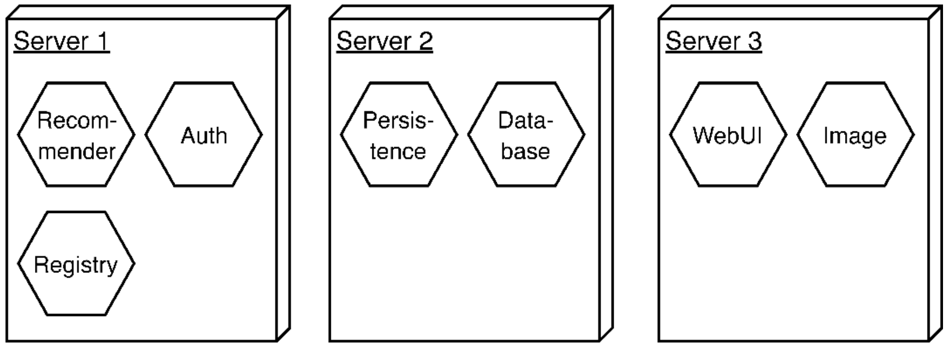


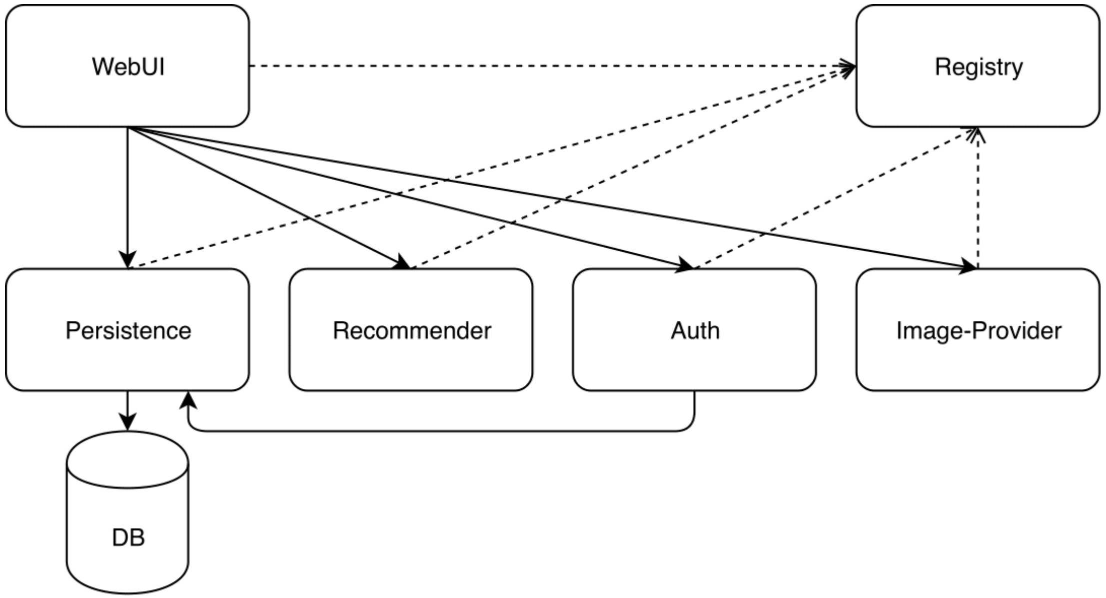



- Higher loads lead to less accuracy; however the effect is light
- All relevant dependencies are still found

# Evaluation Challenges

- Distributed deployment of TeaStore [vKE+18] application



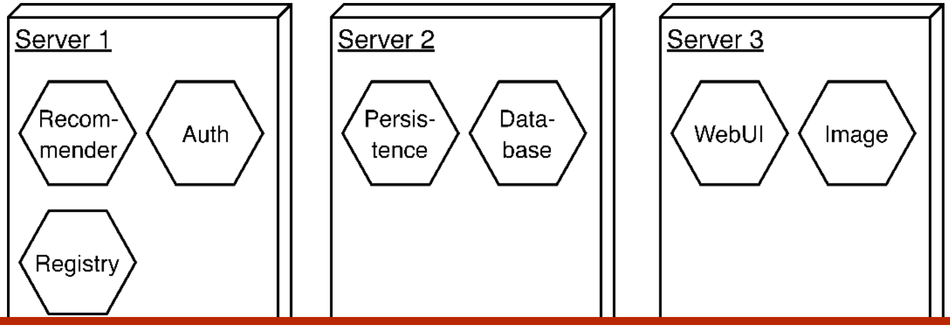




- Locust as load driver with typical behavior of customer
  - Login & logout
  - Browse for products
  - Add products to cart
  - Checkout cart

# Evaluation Challenges



- Distributed deployment of TeaStore [vKE+18] application

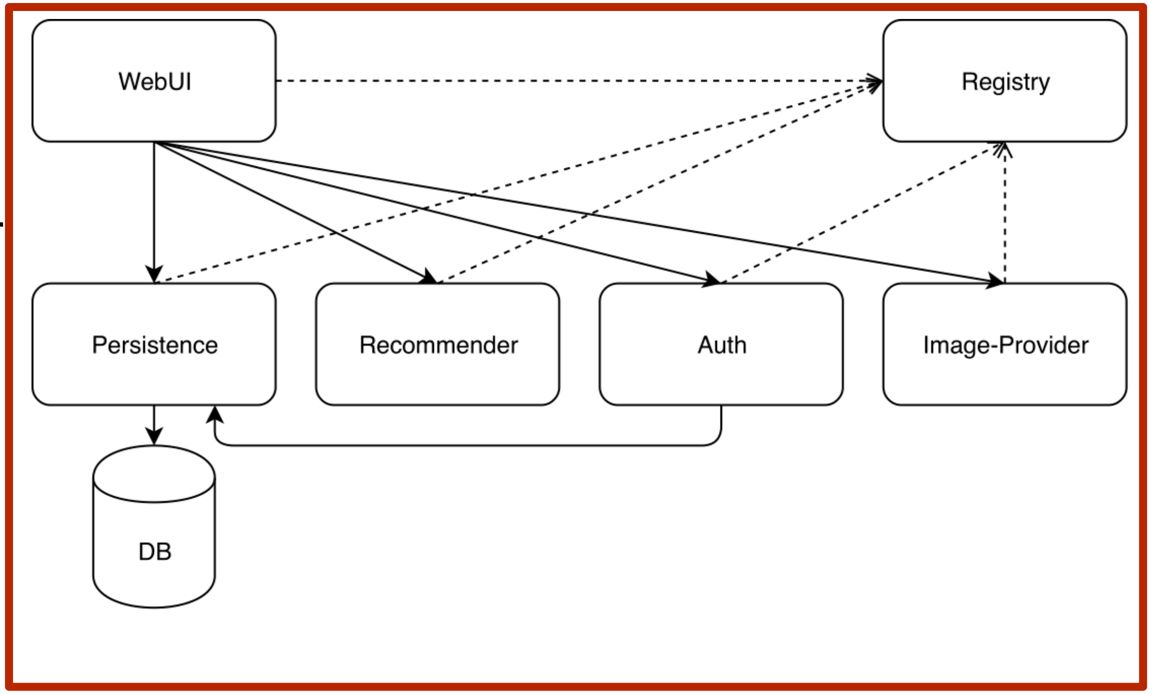



**We need dependencies as gold standard.**

**How can they be achieved?**

**Comparison with other paradigms required?**

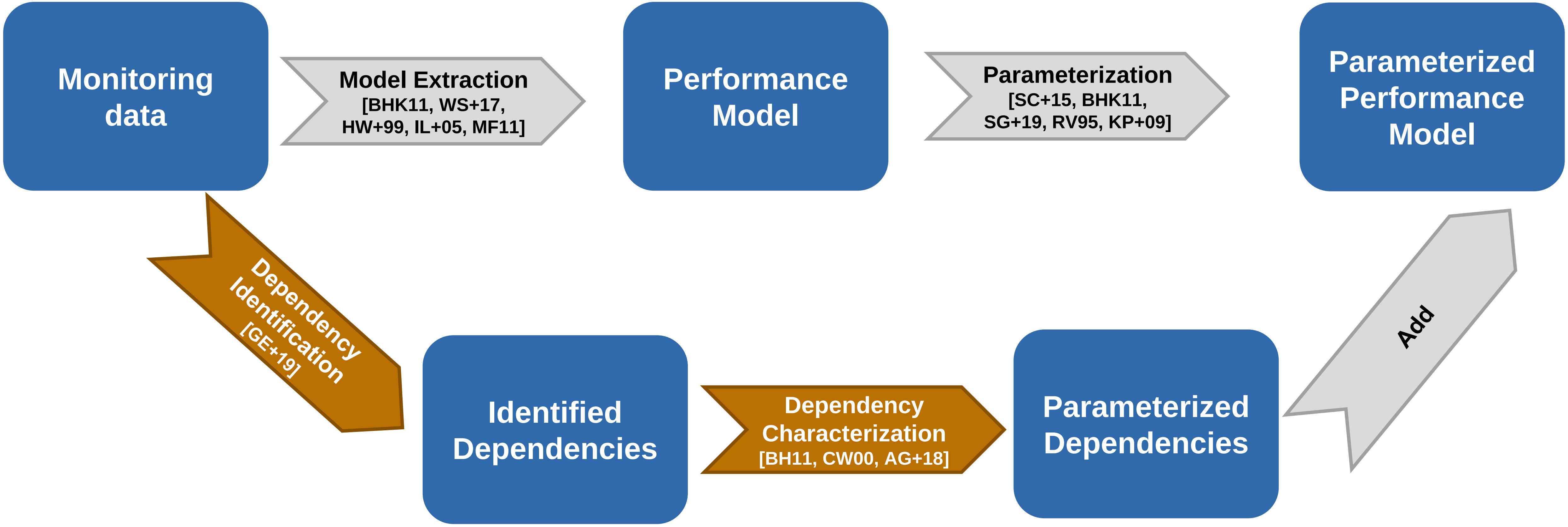
er




  - Add products to cart
  - Checkout cart

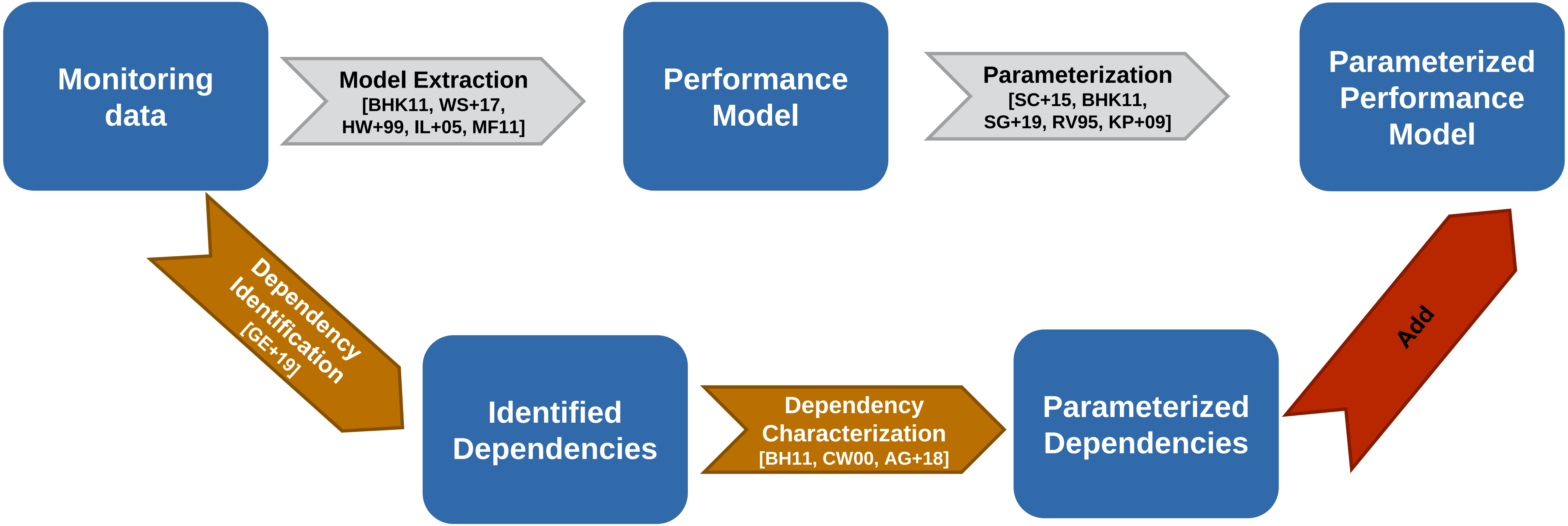
# Integration Challenges





# Integration Challenges





# Conclusion

# Conclusion



**Problem**

**Manual identification of parametric dependencies is not always possible, time-intensive and error-prone**

# Conclusion



| | |
|---|---|
| **Problem** | **Manual identification of parametric dependencies is not always possible, time-intensive and error-prone** |
| **Idea** | **Learning of dependencies using standard monitoring data collected during production** |

# Conclusion



**Problem**: Manual identification of parametric dependencies is not always possible, time-intensive and error-prone

**Idea**: Learning of dependencies using standard monitoring data collected during production

**Benefit**: Increase model accuracy and expressiveness, additional step towards autonomic model learning

# Conclusion



| | |
|---|---|
| **Problem** | **Manual identification of parametric dependencies is not always possible, time-intensive and error-prone** |
| **Idea** | **Learning of dependencies using standard monitoring data collected during production** |
| **Benefit** | **Increase model accuracy and expressiveness, additional step towards autonomic model learning** |
| **Action** | **Use feature selection techniques for detecting, regression for characterizing the dependencies** |

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# Thank you for your attention! ☺

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